PERFORMANCE ANALYSIS OF PROCESS USING MODEL PREDICTIVE CONTROLLER STRATEGY

Thesis submitted in partial fulfillment of the requirements for the degree

Of

Master of Technology

In

Electronics and Instrumentation

By

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Department of Electronics and Communication Engineering

National Institute Of Technology Rourkela

2011-2013

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Under the Guidance of

Prof. T. K. DAN

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NATIONAL INSTITUTE OF TECHNOLOGY

ROURKELA

CERTIFICATE

This is to certify that the thesis titled "**PERFORMANCE ANALYSIS OF PROCESS USING MODEL PREDICTIVE CONTROLLER STRATEGY"** submitted by **Mr. GOVINDARAJULU SIMMA** in partial fulfillment of therequirements for the award of Master of Technology degree in **Electronics &Communication Engineering** with specialization in "**Electronics and Instrumentation**" during session 2011-2013 at **National Institute Of Technology, Rourkela** (Deemed University) is an authentic work by him under my supervision and guidance.

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Abstract

Distillation is a method of separating mixtures based on different in their boiling points. It is a physical separation and not a chemical operation. McCabe-Thiele method used to find the no of trays in a distillation column of tray type distillation column. In this thesis we will see how and why certain variables may be manipulated to control product composition in distillation column, to control distillation column we used model predictive control.

Model predictive control (MPC) has become the leading form of advanced multi variable control technique in process industry. With the help of this thesis we want to presents reliable tuning strategy for unconstrained single input single out put (SISO) dynamic matrix control (DMC). The tuning strategy achieves set point with minimal over shoot and modest manipulate input move sizes and it applicable to a broad class of open loop stable process.

We used DMC algorithms for model control algorithm; in this thesis explain Single input Single output and Multi input and Multi output DMC algorithms.

This thesis presents a model predictive control strategy for multivariable nonlinear control problems2×2,3×3 and 4×4process in distillation column,also explain how the tuning parameters affect the step response model of water heater.

The aim is to provide a solution to nonlinear control problem that is favorable in terms of industrial implementation. MPC TOOLS of MATLAB® has used to simulate the all process.

Key words:

Distillation Column, Water heater, MPC, DMC, SISO, MIMO.

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CHAPTER -1

INTRODUCTION

CHAPTER 1

1.1 Background

Distillation is a process in which a liquid or vapor mixture of two or more substances is substances is separated into its component fractions of desired purity by application and removal of heat. It is well known that pure liquids exhibit different volatilities (i.e. vapor pressure) at a given temperature, and thus if heat is applied to a liquid mixture of these substances, the vapor so generated will be richer in the more volatile substances –those having higher vapor pressures. If this vapor is condensed, it should be clear that a certain amount of purification will be achieved. This is the basic principle underlying a distillation operation [1].

A distillation process may be classified in one of two ways: Binary distillation refers to the separation of two substances and multi component distillation involves more than two substances.

In most of the Biochemical and Chemical processes it is of fundamental importance to control the temperature at which various processes occur. Improper temperature control may lead to loss of product quality means non-profitable operation sometimes create hazardous situations [23]

Model predictive control (MPC) refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant. At each control interval an MPC algorithm attempts to optimize future plant behavior by computing a sequence of future manipulated variable adjustments. The first input in the optimal sequence in then sent into the plant, and the entire calculation is repeated at subsequent control intervals. MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive, and aerospace applications [2].

MPC controller offers better control performance than PI/PID controller especially in multivariable process.

1.2 Motivation:

Most of the techniques presented in market have been based on continuous-time models. The controllers are normally implemented by microprocessors and, therefore, must be converted to discrete time before implementation. We have focused on continuous time because few changes in the techniques are needed for the discrete-time case. One advanced control technique that has solely had discrete-time application is model predictive control (MPC). MPC is by far the most commonly applied advanced control technique in the chemical process industry, so here MPC design for distillation column. One major contributor to the success of MPC is the ability to handle constraints in an optimal fashion. The optimization–based procedure is intuitive and is also a natural way of handling multivariable systems. Distillation column is a multi-input and multi output instruments which have five control variables and five manipulated variable, because of this MPC is applied for distillation column.

1.3 Thesis Organization

Chapter-1 Introduction

Chapter -2 A Study of distillation Column and water heater

This chapter deals with introduction of distillation column basic structure and terminology construction stage. McCabe Thiele method used to find number of tray of tray type distillation column, also deal distillation control concept and also deals water heater and continuous stirred tank reactor.

Chapter-3 Control Strategy of distillation column

This chapter deals with how and why certain variables may be manipulated to control one or both product compositions in a distillation tower. For simplicity we will consider the separation of a single binary feed F into two products D and B.

Chapter-4 Study of MPC and DMC

This chapter deals with basic concept of model predictive control (MPC) limitation and objective function, DMC algorithm also deal here.

Chapter-5 Design Parameters

This chapter deals with design parameters of model predictive control like prediction horizon, control horizon, sampling time, model horizon, input and output weight.

Chapter-6 Distillation column Implementation

This chapter deals with effect of tuning parameters like move suppression, control horizon, prediction horizon and time period, also control$2 \times 2, 3 \times 3$ and 4×4 process distillation column.

Chapter-7 Water heater Implementation

This chapter deals with design parameters of model predictive control like prediction horizon, model horizon, control weight and smoothing factor on step response model of water heater.

Chapter-8 Conclusion and scope for future work

The concluding remarks for all the chapters are presented in this chapter. It alsocontains some future research topics which need attention and further investigation.

CHAPTER-2

INTROUDUCTION OF DISTILLATION COLUMN

CHAPTER 2

2.1 Introductions

The process of distillation should be familiar to most readers. The basic concept is that we can separate a mixture of two pure liquids with different boiling points by heating the mixture to a temperature between their respective boiling points. For example, water boils at 100°C and ethanol boils at around 83°C at atmospheric pressure. If we heat the mixture to say 92°C, the ethanol will boil and be transformed into vapor (which is collected and condensed) while the water will remain as a liquid. This phenomenon is usually quantified by the relative volatility of the two components.

2.1.1 Distillation Equipment

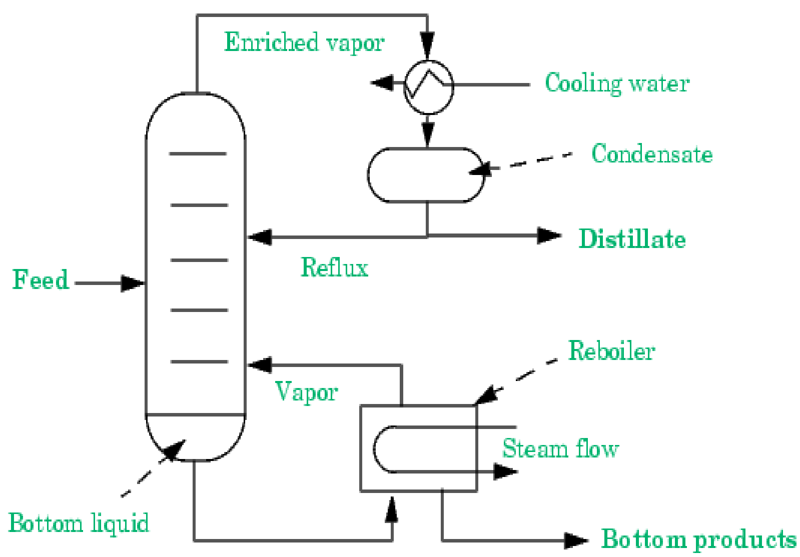


Figure2.1 schematic of a typical distillation column

The schematic diagram of a typical distillation column is shown below figure 2.1. The equipment consists of a vertical shell with a number of equally spaced trays mounted inside of it. Each tray contains two conduits, one on each side, called down comers. Liquid flows through these down comes by gravity from each tray to the one below. The vertical shell is connected by suitable piping to a heating device called a reboiler.Reboiler to provide the necessary vaporization for the distillation process.The condenser to cool and condense the vapor leaving the column from top. The Reflux drums to hold the condenser vapor from the top of column so that liquid (reflux) can be recycled back to the column. The vertical shell together with the condenser and reboiler constitute a distillation column [1].

2.1.2 Basic operation and terminology

The liquid mixture that is to be processed is known as the feed and this is introduced usually somewhere near the middle of the column to a tray known as the feed tray. The feed tray divides the column into a top (enriching or rectification) and a bottom (stripping) section shown in figure 2.2. The feed flows down the column where it is collected at the bottom in the reboiler.

Heat is supplied to the reboiler to generate vapor. The source of heat input can be any suitable fluid, although in most chemical plants this is normally steam. In refineries, the heating source may be the output streams of other columns. The vapor raised in the reboiler is re-introduced into the unit at the bottom of the column. The liquid removed from the reboiler is known as the bottoms product or simply, bottoms. The vapor moves up the column, and as it exits the top of the unit, it is cooled by a condenser. The condensed liquid is stored in a holding vessel known as the reflux drum. Some of this liquid is recycled back to the top of the column and this is called the reflux. The condensed liquid that is removed from the system is known as the distillate or topproduct.

Thus, there are internal flows of vapor and liquid within the column as well as external flowsof feeds and product streams, into and out of the column.

2.2 Graphical methods for find no of tray

The number of tray in tray type distillation column is important design parameter. No of tray we can find either analytical of Graphical method. There are two graphical methods are McCabe-Thiele method and the Ponchon-Savarit method. Separation of a binary mixture can be achieved in a single-stage process known as the equilibrium flash. If enhanced separation is desired, a column containing a suitable number of trays must be used.

Here we review only McCabe-Thiele method, which utilizes an x-y diagram.

2.2.1 McCabe-Thiele method

This method can be used when the following conditions are satisfied [2].

1. Molal heats of vaporization of the two substances are roughly the same
2. Heat effects (heats of solution, heat losses to and from column) are negligible.

These so-called constant-molal overflow assumptions imply that for every mol of vapor condensed, 1 mol of liquid is vaporized. Thus the liquid and vapor rates within each section of the tower remain constant.

The McCabe-Thiele method utilizes material balances and equilibrium relationships. These relationships are written for the enriching section and the stripping section and then combined to solve the binary distillation problem.

McCabe-Thiele method understands with this problem [2], methanol and water are too separated in a fractionation column operating at 1 atm. The feed is 50 percent vapor and has a methanol mole fraction of 0.60. The saturated liquid distillation must contain 95 % methanol and the bottom have 3% methanol. If the reflux ratio is twice than find no of tray feed point location [1].

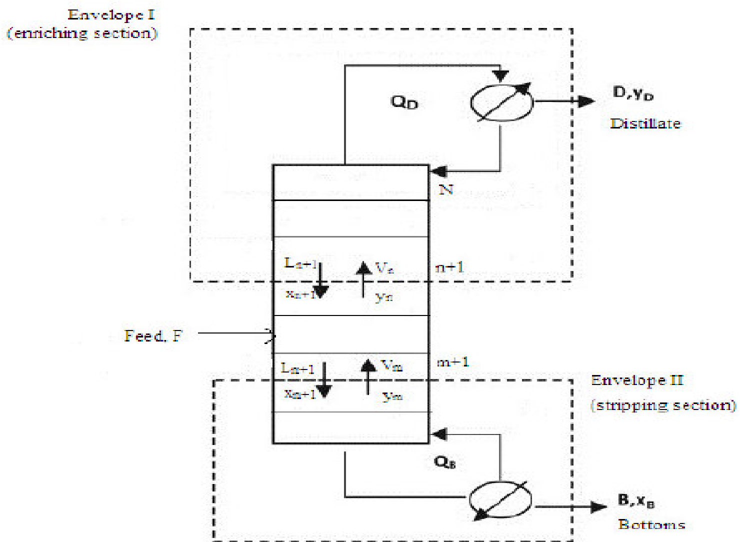


Figure 2.2 Material-balance envelopes for operating lines

2.2.2 Enriching and stripping section

Referring to figure 2.2, a component material balance around a general tray *n* in the enriching section is written as:

$$V_n y_n = L_{n+1} x_{n+1} + D x_D \quad (2.1)$$

The trays are numbered from the bottom up. As per the assumption molal overflow, the subscripts of L and V are dropped. Equation (2.1) may be written as

$$V y_n = L x_{n+1} + D x_D \quad (2.2)$$

Now solving for $y_n$to give

$$y_n = \frac{L}{V} x_{n+1} + \frac{D}{V} x_D (2.3)$$

On x-y coordinates equation (2.3) is a straight –line of slope L/V with a y-intercept of x_DD/V. it relates the composition of the more volatile component in the vapor stream leaving a general tray *n* in the enriching section to that of the liquid entering tray *n*. This straight line, which represents the operating line for enriching section of the tower shown in Figure 2.3

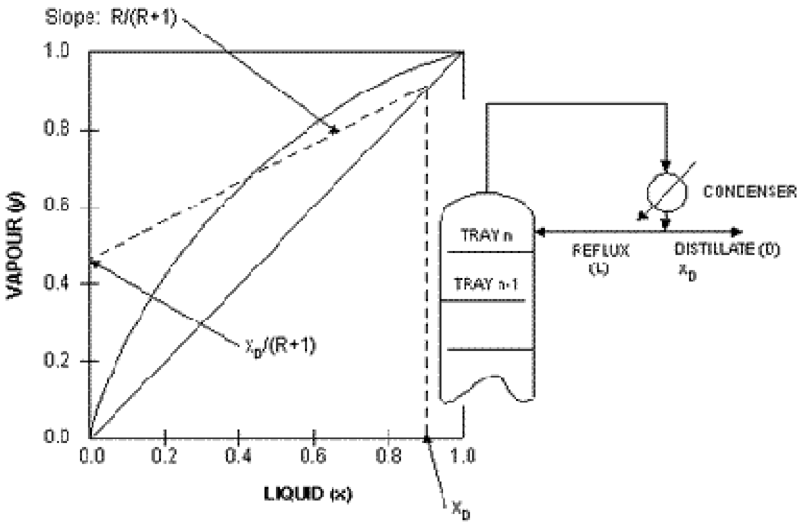


Figure 2.3 Enriching-section operating line

Similarly the equation for the stripping-section operating line can be developed by component material balance around envelope II in Figure 2.4

$y_m = \frac{\bar{L}}{\bar{V}} x_{m+1} - \frac{B}{\bar{V}} x_B$(2.4)

Where the bar indicates that the stream is in the stripping section. This equation relates the composition of the more volatile component in the vapor stream leaving tray *m* in the stripping section to that in the liquid entering tray *m.* stripping section operating line has a slope of $\frac{\bar{L}}{\bar{V}}$ and it intersects the diagonal, where x=y, at x_B as shown in Figure 2.4.

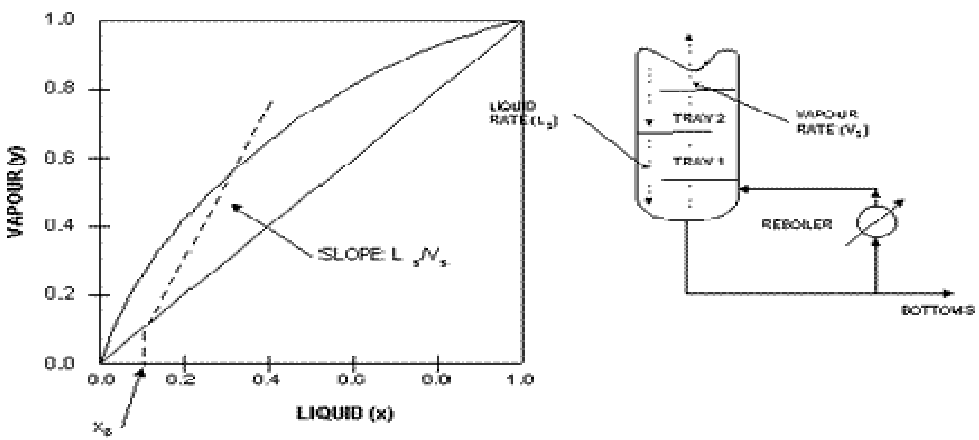


Figure 2.4 stripping-section operating line

2.2.3 Construction of a stage

The operating line, either (2.3) or (2.4), is used in conjunction with curve to locate equilibrium curve to locate an equilibrium stage on an x-y diagram as shown in Figure 2.5

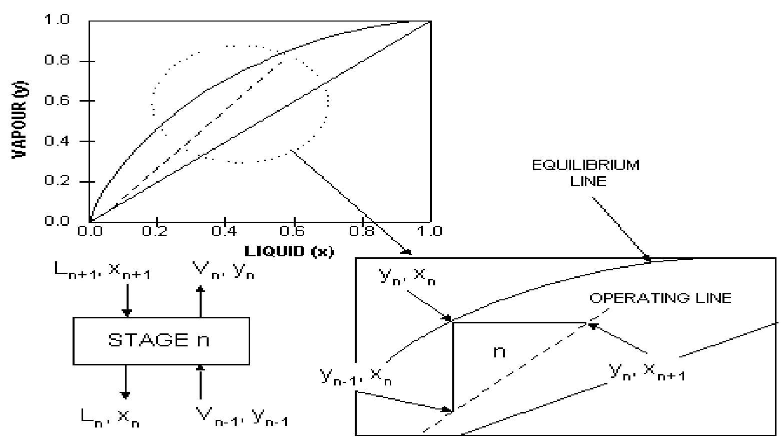


Figure 2.5 construction of stage

A point on the operating line gives x_{n+1}, y_n corresponding to the composition of the two streams L_{n+1}, V_n passing stage *n*. Thus the triangle shown in Figure 2.7 represents stage n. This type of graphic construction will be necessary to determine the number of ideal trays required for a specified separation.

The enriching-section operating line intersects the stripping-section operating line at the feed tray. The equation of the feed line at which these two lines intersect may be derived by combining the material-balance equations for the feed tray:

$\bar{L} = L + qF$ (2.5)

And

$\bar{V} = V - (l - q)F$(2.6)

Where q=fraction of feed that is liquid

Depending on the state of the feed, the feed lines will have different slopes. For example,

q = 0 (saturated vapor)
q = 1 (saturated liquid)
0 < q < 1 (mix of liquid and vapor)
q> 1 (sub cooled liquid)
q< 0 (superheated vapor) [1]

The q-lines for the various feed conditions are shown in Figure 2.6

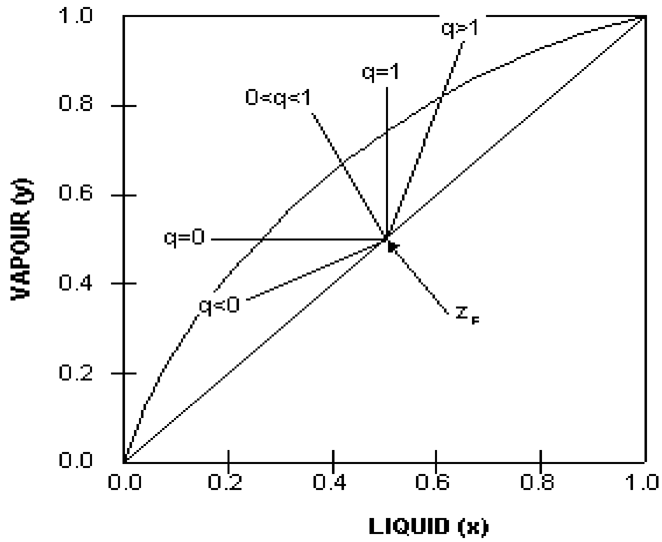


Figure 2.6 Feed lines

Now recall enriching- and stripping-section operating line equations are, respectively

$Vy_n = Lx_{n+1} + Dx_D$ (2.3)

And

$\bar{V}y_m = \bar{L}x_{m+1} - Bx_B$ (2.4)

These two lines intersect at a point where the x's and y's become identical. Subtracting equation (2.4) from equation (2.3) gives

$$(V - \bar{V})y = (L - \bar{L})x + Dx_D + Bx_B \quad (2.7)$$

The equation (2.7) can be written in the view of equation (2.5) and (2.6) as

$$(1 - q)Fy = -qF_x + Fz_F$$

Or

$y = \frac{q}{q-1}x - \frac{z_F}{q-1}$ (2.8)

The equation (2.8) is the equation of the feed line having a slope of q/q-1 and an intercept on the x=y diagonal al z_F. The q lines for the various types of feed are shown in Figure 2.6.

For an optimum design that requires the fewest number of stages, the feed tray must be placed at the correct location. To determine the number of stages required for a specified separation, the procedure is to locate x_D, x_B, $z_F$on the diagonal; draw the feed line; the enriching-section operating line, and the stripping-section operating line; and then step off the stages. An illustrative plot for distillation column which solve above problem get 11 no of tray, and fed position is 5 from enriching section.

2.3Water heater

Water heating is a thermodynamic process that uses an energy source to heat water above its initial temperature. Typical domestic uses of hot water include cooking, cleaning, bathing, and space heating. In industry, hot water and water heated to steamhave many uses.

Water is heated in vessels known as water heaters, kettles, pots, or coppers. Metal vessels that heat a batch of water do not produce a continual supply of heated water at a preset temperature. Rarely, hot water occurs naturally, usually from natural hot springs. The temperature varies based on the consumption rate, becoming cooler as flow increases.

Appliances that provide a constant supply of hot water are variously called water heaters, hot water heatersor tanks, boilers, heat exchangers. These names depend on region, and whether they heat potable or non-potable water, are in domestic or industrial use, and their energy source.. Electricity to heat water may also come from any other electrical source, such as nuclear power or renewable energy. Alternative energy such as solar energy, heat pumps, hot water heat recycling, and geothermal heating can also heat water, often in combination with backup systems powered by fossil fuels or electricity.

2.3.1Some types of water heaters

2.3.2 Storage water heaters (tank-type)

Most water heaters are tank type in house hold applications. Also called storage water heaters, these consist of a cylindrical vessel or container in which water is kept continuously hot and ready for use. These may use electricity, natural gas, propane, heating oil, solar, or other energy sources.

2 .3.3Tankless heaters

Tank less water heaters also called continuous, instantaneous, inline, on demand, or instant on water heaters are gaining in popularity. These high-power water heaters instantly heat water as it flows through the device, and do not retain any water internally except for what is in the heat exchanger coil. Copper heat exchangers are preferred in these units because of their high thermal conductivity and ease of fabrication.

2.3.4 Solar water heaters

Increasing solar powered water heaters are being used. Their solar collectors are installed outside dwellings, typically on the roof or walls or nearby, and the potable hot water storage tank is typically a pre-existing or new conventional water heater, or a water heater specifically designed for solar thermal.

2.4 Step response model of a water heater[22]

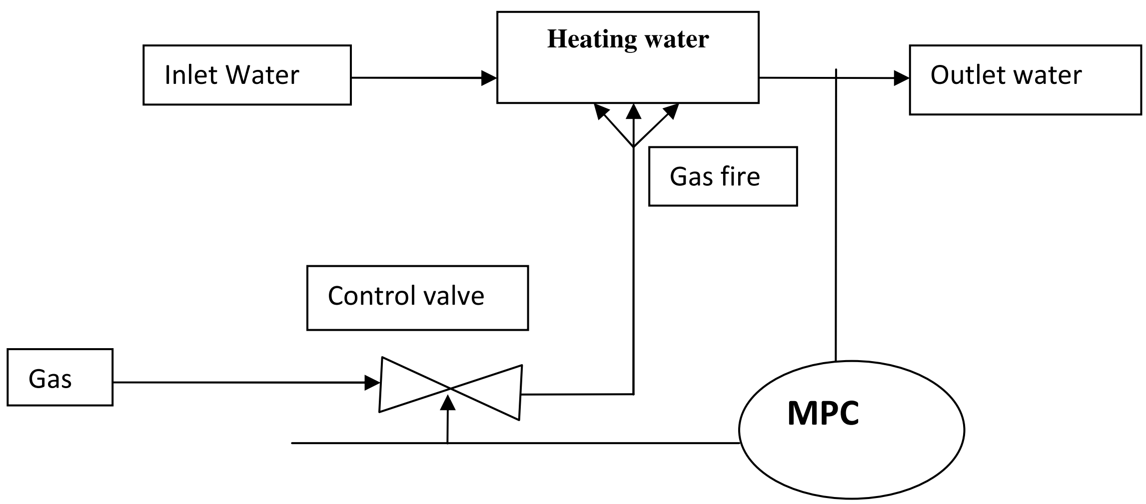


Fig 2.7 Step response model of water heater

In most of the Biochemical and Chemical processes it is of fundamental importance to control the temperature at which various processes occur. Improper temperature control may lead to loss of product quality means non-profitable operation sometimes creates hazardous situations.

Temperature is generally controlled by modifying the power output of a heating/cooling device. This translates in setting the flow rate of a heating/cooling agent or the electrical current applied to an electrical heat.

Control valves are valves used to control conditions such as pressure,flow, liquid level and temperatureby fully or partially opening or closing in response to signals received from controllers that compare a "set point" to a "process variable" whose value is provided by sensors that monitor changes in such conditions.

The closing or opening of control valve done automatically by electrical, pneumatic or hydraulic actuators. Positioners are used to control the closing or opening of the actuator based on electric or pneumatic signals

Cold water is heated by gas burner. The aim of DMC is by manipulating valve to control the gas flow so that the outlet temperature at desired level.

Gas fire is used to heat the water .Gas fire can be controlled by the control valve according to the MPC response .Out let temperature is measured by a thermocouple or any other temperature measuring device. This variable is the controlled variable. Temperature required is the set point of the model predictive controller; this is also a manipulated variable for the MPC.

CHAPTER -3

CONTROL STRATEGY OF DISTILLATION COLUMN

Here we will see how and why certain variables may be manipulated to control one or both product compositions in a distillation tower. For simplicity we will consider the separation of a single binary feed F into two products D and B. schematic of the tower is shown in the

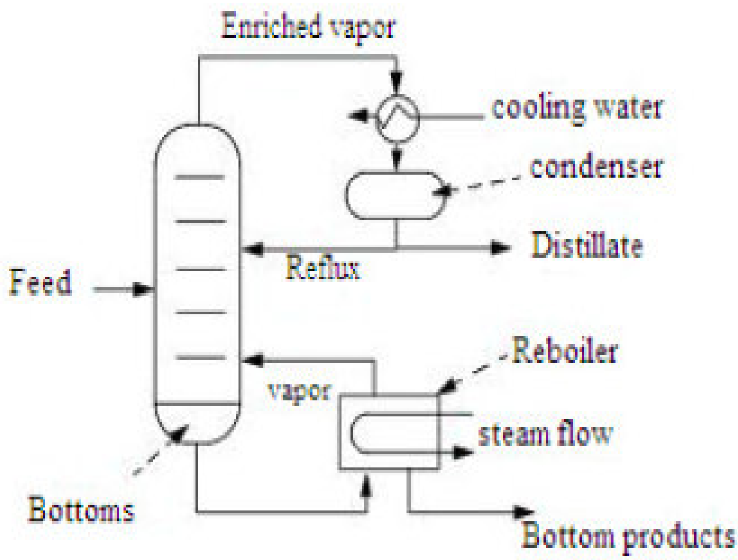


Figure 3.1 schematic of a distillation tower

The overall material balance for this column may be expressed as

$$F = D + B \quad (3.1)$$

The component material balance for the more volatile substance, which we donate as substance A, is

$$Fx_F = Dx_D + Bx_B \quad (3.2)$$

The term B in the equation (3.2) may be replaced by F-D in accordance with equation (3.1) to give

$$Fx_F = Dx_D + (F - D)x_B$$

Or

$$\frac{D}{F} = \frac{x_F - x_B}{x_D - x_B} \quad (3.3)$$

Equation (3.3) gives the unique steady-state relationship between D/F and x_D, x_B, x_F.

Similarly, if we had replaced D in the equation (3.2) by F-B, we will get

$\frac{B}{F} = \frac{x_D - x_F}{x_D - x_B}$(3.4)

Equation (3.4) gives the unique steady-state relationship between B/F and x_D, x_B, x_F.

Typically the control objectives in a distillation operation are to maintain $x_D$and/or $x_B$at set point in the presence of disturbances. These disturbances may be characterized as (1) process loads, (2) changes in cooling- and heating-medium supply conditions, and (3) equipment fouling.

Our control objectives are to maintain x_D and/or x_B constant in the presence of changes in F and x_F.

But distillation columns are not always at steady-state because of the disturbances. Therefore, we need to know which variables to manipulate to control x_D and/or x_B at their steady state values in the presence of disturbances.

Thus if a saturated liquid feed F_s with composition x_{Fs} is feed to a distillation column having N ideal stages operating at steady state and the reflux rate is L_s and the vapor boilupV_s, then the column will produce two products, D_s and B_s, that have compositions x_{Ds} and x_{Bs} respectively.

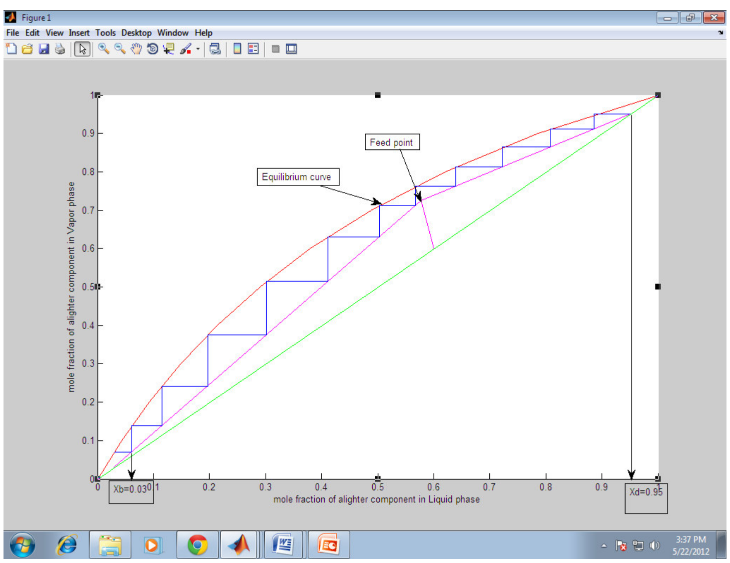


Figure 3.2 McCabe-Thiele diagram

To solve this control problem, we begin with the examination of equation (3.3):

$\frac{D}{F} = \frac{x_F - x_B}{x_D - x_B}$ (3.3)

This equation suggests that for a given F and x_F, a change in D affects x_D and/or x_B. Therefore, we may postulate that when changes in F or x_F occur, it may be possible to manipulate D so as to control x_D or x_B. But here in equation (3.3) there are two unknowns (x_D and x_B) so we cannot assess the quantitative effects of changes of D upon x_D and/or x_B.

Another relationship is found from McCabe-Thiele diagram between vapor or (reflux) flow to the two compositions. Several investigators derived relationship from many examines.

One such relationship is

$$\frac{V}{F} = \frac{(R_m+1)\frac{D}{F}}{1-1.6612\left[\frac{\frac{\ln S}{\ln \alpha}+1}{N+1}-0.25\right]^{1.7643}} \quad [3] \qquad (3.5)$$

Where R_m is the minimum reflux ratio given by

$$R_m = \left(\frac{1}{\alpha-1}\right)\left(\frac{x_D}{x_F} - \frac{\alpha(1-x_D)}{1-x_F}\right) \quad [2] \qquad (3.5a)$$

And S is called "separation factor," which is defined as

$$S = \frac{x_D(1-x_B)}{x_B(1-x_D)} \qquad (3.5b)$$

Equations (3.3) and (3.5) completely describe the effect of changing D and/or V (or equivalently D/F or V/F) upon x_D and x_B. For a given upset in F or x_F, these equations will tell us how to control x_D and/or x_B.

3.1 Control of x_D or x_B for upsets in F

This is a single composition-control problem. Here we can easily show that $x_D$can be maintained at set point by manipulating D while holding V constant. For this case we write equations (3.3) and (3.5) as

$$\frac{D}{F} = \frac{x_{F_S}-x_B}{x_{D_S}-x_B} \qquad (3.6)$$

$$\frac{V_S}{F} = \frac{(R_{m_0}+1)\left(\frac{x_{F_S}-x_B}{x_{D_S}-x_B}\right)}{1-1.6612\left[\frac{\frac{\ln S}{\ln \alpha}+1}{N+1}-0.25\right]^{1.7643}} [3] \qquad (3.7)$$

The subscript s in equation (3.7) denotes that steady-state value of the variables. For the new values of F, equation (3.7) gives the new value of x_B, this x_B substitution in equation (3.6), gives the new value of D requires for control of x_D at x_{Ds}. Since this control strategy calculates a new value of D for the new value of F, the new value of B is given by the overall material balance

$$B = F - D \qquad (3.8)$$

Fig 3.3 clearly show that relation between feed vapor and distillate, feed have linear relation with distillate and vapor.

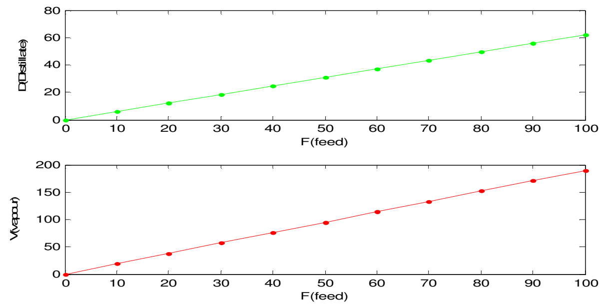


Figure 3.3 control $X_D$and X_B upset F

3.2 Control of x_D or x_B for upsets in x_F

The control system in 3.1 section for control of x_D (or x_B) for upsets in F, also be able to handle upsets in x_F or else a single feedback controller will not be able to hold the composition at the set point for both type of disturbances. Here we see that same control system will work for changes in x_F as well. Equations for control of x_D are

$$\frac{D}{F_S} = \frac{x_F - x_B}{x_{D_S} - x_B} \qquad (3.9)$$

$$\frac{V_S}{F_S} = \frac{(R_m+1)\left(\frac{x_F - x_B}{x_{D_S} - x_B}\right)}{1-1.6612\left[\frac{\frac{\ln S}{\ln \alpha}+1}{N+1} - 0.25\right]^{1.7643}} \text{ [3]} \qquad (3.10)$$

For controlled values of x_D, that is, x_{Ds}, the required value of D and the resulting value of x_B may be obtained by equation (3.9) and (3.10). Thus the control strategy that we proposed for control of x_D for upsets in F will function for upsets in x_F as well.

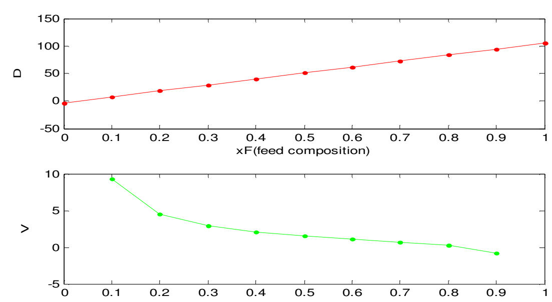


Figure 3.4 controls D and V upset X_F

Above figure3.4 show the relation between X_F and V or X_F and D which is clearly show that the relation between feed composition and distillate is linear but in the case of feed composition vapour starting nonlinear but after some time it becomes linear.

CHAPTER-4

STUDY OF MPC AND DMC

CHAPTER 4

4.1 Introduction

The basic MPC concept can be summarized as follows. Suppose that we wish to control a multiple-input, multiples-output process while satisfying inequality constraints on the input output variables. If a reasonably accurate dynamic model of the process is available, we can use the model and current measurement to predict future value of the outputs. Then the appropriate changes in the input variable can be calculated based on the both prediction and measurement. In essence, the changes in the individual input variables are coordinate after considering input-output relationships represented by the process model. In MPC applications, the output variable also referred to as controlled variables a based or CV, while the input variables are also called manipulated variables or MV. Measured disturbance variables are called DV or feed forward variables. We will use these term. Model predictive control offers several important advantages:

(1) The process model captures the dynamic and static interaction between input, output, and disturbance variables.

(2) Constraints on input and outputs are considered in a systematic manner.

(3) The control calculations can be coordinated with the calculation set points

(4) Accurate model predictions can provide early warning of potential problems.

4.2Basic block diagram Model Predictive Control

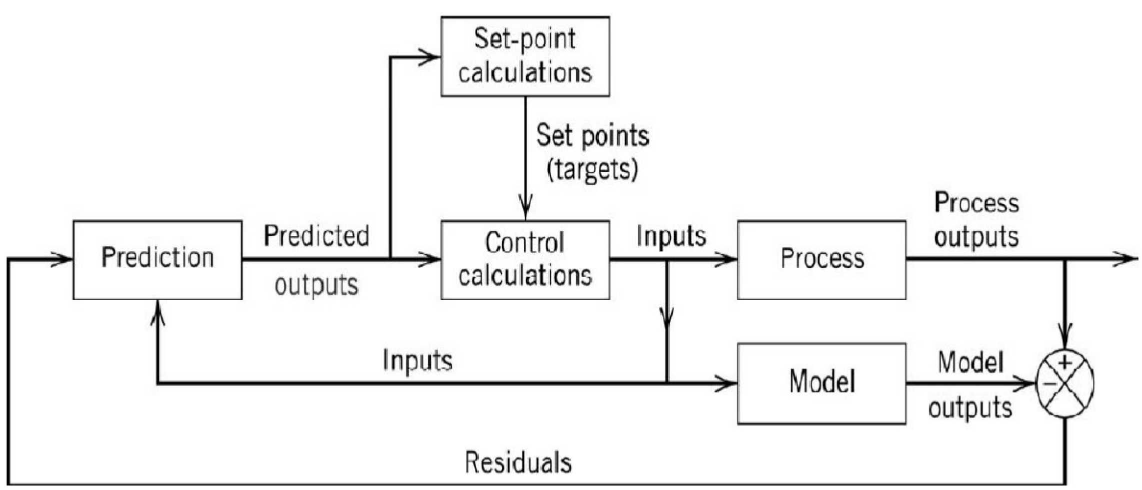
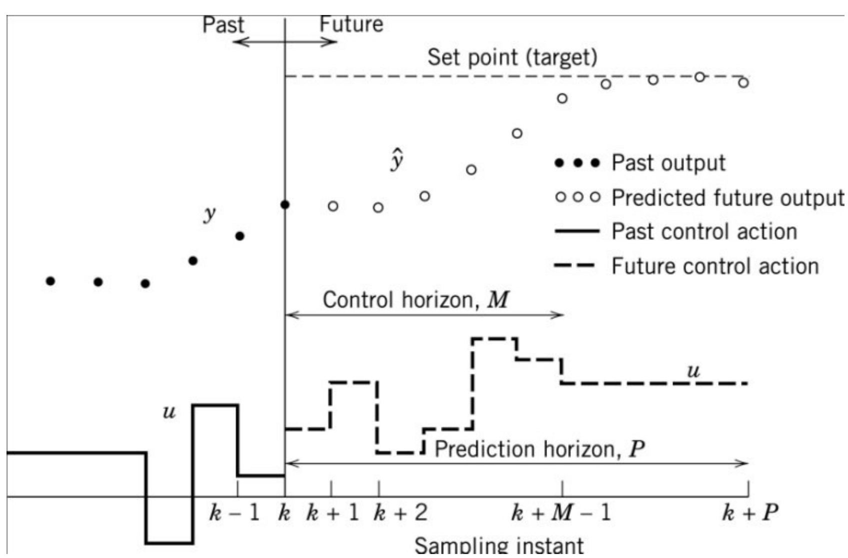


Fig 4.1-Block diagram of MPC[4]

A block diagram of model predictive control system is shown above Fig 4.1 .A process model is used to predict the current values of the output variables. The residuals, the differences between the actual and predicted outputs, serve as the feedback signal to a prediction block. The predictions are used in two types of MPC calculations that are performed at each sampling instant: set point calculation and control calculations. Inequality constraints on the input and output variables, such as upper and lower limits, can be included in either type of calculation. NOTE that MPC configuration is similar to both internal model control configuration and smith predictor configuration because the model acts in parallel with the process and the residual serves as a feedback signal. However, the coordination of the control and set point calculations is a unique feature of MPC. Furthermore, MPC has had a much greater impact on industrial practice than IMC or Smith predictor because it is more suitable for the constrained MIMO control problems.

The set point for the control calculation, also called target, are calculated from an economic optimization based on a steady-state model of the process, traditionally, a linear model. Typically optimization objective include maximizing a profit function, maximizing a cost function, or maximizing a production rate. The optimum values of set points are changed frequently owing to varying process conditions, especially changes in the inequality constraints. The constraint changes are due to variations in process conditions, equipment, and instrumentation, as well as economic data such as prices and costs. In MPC the set point are typically calculated each time the control calculation are performed.

The control calculations are based on current measurements and predictions of the future values of the outputs. The predictions are made using dynamic model, typically a linear empirical model such as a multivariable version of the step response or difference equation models. For non linear process, it can be advantageous to predict future output value using a nonlinear dynamic models and empirical models, such as neural networks, have been used in nonlinear MPC [5] [6].



[7]

Fig 4.2 Basic concept of MPC

The objective of the MPC control calculation is to determine a sequence of control moves (that is, manipulated input changes) so that the predicted response moves to the set points in an optimal manner. The actual output y , predictive output $\hat{y}$, and manipulated input u are shown above Fig

4.2. At the current sampling instant, denoted by k, the MPC strategy calculates a set of M values of the input $\{u(k+i-1), i=1,2,3....M\}$ .The set consists of the current input and future inputs $u(k)$, $M-1$ respectively. The input is held constant after the control moves. The inputs are calculated so that a setoff p predicted outputs $\{\hat{y}(k+i), i=1,2,..P\}$reach the set point in an optional manner. The control calculations are based on optimizing an objective function. The number of prediction p is referred to as the prediction horizon while the number of control moves M is called the control horizon.

A distinguishing feature of MPC is its receding horizon approach. Although a sequence of M control moves is calculated at each sampling instant, only the first moves is actually implanted. Then a new sequence is calculated at the next sampling instant, after new measurements become available; only the first input move is implemented. This procedure is repeated at each sampling instant, after new measurement become available; only the first input move is implemented. This procedure is repeated at each sampling instant.

4.3 Limitation of MPC

Many of the "classical" MPC approaches used in industry have performance limitations, which summarize here.

4.3.1 Model structure.

The finite step and impulse response models limit applications to open-loop stable process and require many model coefficients to describe the response (indeed, even a first order system with two parameters may require 50 or more step response coefficients). Integrating systems have been handled by formulating the derivative of an integrating output as the controlled output.

4.3.2 Disturbance assumption.

Here we assume that output disturbance is constant. This may not yield good performance if the real disturbance occurs at the plant input.

4.3.3 Finite horizons.

Performance could be deteriorating if the prediction or control horizons were not formulated correctly, even if the model was perfect.

4.3.4 Model type.

The step and impulse response model are all linear. For some process (exothermic reactors) where the process operating conditions are change frequently (different product specifications for each consumer, for example), a single linear model may not describe the dynamic behavior of the process over the wide range of conditions. For these systems, better control performance may be achieved if nonlinear model are used.

4.4Control objective function of MPC:

There are several objective functions but, we applied standard least-squares or quadratic programming objective function. QP formulation gives smoother control actions and the MPC will have more intuitive tuning parameters. The QP formulation is used in this thesis. The objective function is a sum of squares of the predicted errors (difference between the set points and the model-predicted outputs) and the control moves (changes in the control action from step to step).

A quadratic objective function for a predictive horizon of 3 and a control horizon of 2 can be written as.

$\varphi = Q(r_{k+1} - \hat{y}_{k+1})^2 + Q(r_{k+2} - \hat{y}_{k+2})^2 + Q(r_{k+3} - \hat{y}_{k+3})^2 + R\Delta u^2{}_k + R\Delta u^2{}_{k+1}$(4.1)

Where $\hat{y}$ represents the model predicted outputs, r is the set point, Δu is the change in manipulated input from one sample time to the next, $Q$and R is a weight for the change in the output and manipulated input respectively.

For a prediction horizon of P and a control horizon$M$, the least square objective function is written as.

$\varphi = Q\sum_{i=1}^{P}(r_{k+i} - \hat{y}_{k+i})^2 + R\sum_{i=0}^{M-1}\Delta u^2{}_{k+i}$ (4.2)

The optimization problem solved is usually stated as a minimization of the objective function, obtained by adjusting the M control moves.

One limitation of output weight is we cannot take null matrix.

4.5Dynamic Matrix Control

DMC was developed by shell Oil Company in 1960s and 1970s [8]. It is based on a step response model. Key features of the DMC control algorithm is

1. Linear step response model for the plant.
2. Quadratic performance objective over a finite prediction horizon.
3. Future plant output behavior specified by trying to follow the set point as closely as possible.

$$\hat{y}_k = S_1\Delta u_{k-1} + S_2\Delta u_{k-2} + \cdots\cdots\cdots\cdots\cdots + S_{N-1}\Delta u_{k-N+1} + S_N u_{k-N} \quad (4.3)$$

Where is written in the form

$$\hat{y}_k = \sum_{i=1}^{N-1} S_i\,\Delta u_{k-i} + S_N u_{k-N} \quad (4.4)$$

Where $\hat{y}_k$the model prediction at time is step$k$, and u_{k-N} is the manipulated input N steps in the past$\Delta u(k-i+1) = u(k-i+1) - u(k-i)$.

Note that the model-predicted output is unlikely to be equal to the actual measured output at time step$k$. The difference between the measured output (y_k) and model prediction is called the additive disturbance.

$d_k = y_k - \hat{y}_k$ (4.5)

Consider corrected prediction is then equal to the actual measured output at step k

$\hat{y}^c{}_k = \hat{y}_k + d_k$(4.6)

Similarly, the corrected predicted output at the first time step in the future can be found from

$\hat{y}^c{}_{k+1} = \hat{y}_{k+1} + \hat{d}_k$(4.7)

From equation (4.4) and (4.7) we can write as

$\hat{y}^c{}_{k+1} = \sum_{i=1}^{N-1} S_i \, \Delta u_{k-i+1} + S_N u_{k-N+1} + \hat{d}_{k+1}$(4.8)

$\hat{y}^c{}_{k+1} = S_1 \Delta u_k + \sum_{i=2}^{N-1} S_i \, \Delta u_{k-i+1} + S_N u_{k-N+1} + \hat{d}_{k+1}$(4.9)

$\hat{y}^c{}_{k+2} = S_1 \Delta u_{k+1} + S_2 \Delta u_k + \sum_{i=3}^{N-1} S_i \, \Delta u_{k-i+2} + S_N u_{k-N+2} + \hat{d}_{k+1}$ (4.9b)

In similar fashion we can find j th step in to the future

$\hat{y}^c{}_{k+j} = \sum_{i=1}^{j} S_i \, \Delta u_{k-i+j} + \sum_{i=j+1}^{N-1} S_i \, \Delta u_{k-i+j} + S_N u_{k-N+j} + \hat{d}_{k+j}$(4.10)

$\sum_{i=1}^{j} S_i \, \Delta u_{k-i+j}$ {Effect of current and future moves

$\sum_{i=j+1}^{N-1} S_i \, \Delta u_{k-i+j} + S_N u_{k-N+j}$ {Effect of past moves

$\hat{d}_{k+j}${Correction term

We here assume that correction term is constant in the future

$\hat{d}_{k+j} = \hat{d}_{k+j-1} = \cdots \cdots = d_k = y_k - \hat{y}_k$(4.11)

Also, realize that there are no control moves beyond the control horizon of Msteps, so

$\Delta u_{k+M} = \Delta u_{k+M+1} = \cdots \cdots = \Delta u_{k+P-1} = 0$(4.12)

In matrix form, for prediction horizon of P steps and a control horizon of M steps

$$\underbrace{\begin{bmatrix}\hat{y}^c_{k+1}\\ \hat{y}^c_{k+2}\\ \vdots\\ \hat{y}^c_{k+j}\\ \vdots\\ \hat{y}^c_{k+P}\end{bmatrix}}_{\substack{P\times 1\\ \text{corrected output}\\ \text{prediction}.\,\hat{y}^c}} = \underbrace{\begin{bmatrix} s_1 & 0 & 0 & \cdots & 0 & 0\\ s_2 & s_1 & 0 & \cdots & 0 & 0\\ \vdots & \vdots & & & & \\ s_j & s_{j-1} & s_{j-2} & \cdots & \cdots & s_{j-M+1}\\ \vdots & \vdots & \vdots & & & \vdots\\ s_P & s_{P-1} & s_{P-2} & \cdots & \cdots & s_{P-M+1}\end{bmatrix}}_{\substack{P\times M\\ \text{dynamic matrix}.\, s_f}} \underbrace{\begin{bmatrix}\Delta u_k\\ \Delta u_{k+1}\\ \vdots\\ \Delta u_{k+M-2}\\ \Delta u_{k+M-1}\end{bmatrix}}_{\substack{M\times 1\\ \text{current and future}\\ \text{control moves},\,\Delta u_f}}$$

$$+\underbrace{\begin{bmatrix} s_2 & s_3 & s_4 & \cdots & s_{N-2} & s_{N-1}\\ s_3 & s_4 & s_5 & \cdots & s_{N-1} & 0\\ \vdots & \vdots & & & 0 & 0\\ s_{j+1} & s_{j+2} & \cdots & s_{N-1} & 0 & 0\\ \vdots & \vdots & \vdots & & & \vdots\\ s_{P+1} & s_{P+2} & \cdots & 0 & \ldots & 0\end{bmatrix}}_{\substack{P\times(N-2)\\ \text{matrix}.\, s_{past}}} \underbrace{\begin{bmatrix}\Delta u_{k-1}\\ \Delta u_{k-2}\\ \vdots\\ \Delta u_{k-N+3}\\ \Delta u_{k-N+2}\end{bmatrix}}_{\substack{(N-2)\times 1\\ \text{past control}\\ \text{moves},\,\Delta u_{past}}} + s_N \underbrace{\begin{bmatrix}u_{k-N+1}\\ u_{k-N+2}\\ \vdots\\ u_{k-N+P}\end{bmatrix}}_{\substack{P\times 1\\ \text{past inputs},\,u_p}} + \underbrace{\begin{bmatrix}d_{k+1}\\ d_{k+2}\\ \vdots\\ d_{k+P}\end{bmatrix}}_{\text{predicted disturbances},\,\hat{d}} \quad (4.13)$$

Above equation (4.13) we can write matrix-vector notation

$$\hat{y}^c = S_f\Delta u_f + S_{past}\Delta u_{past} + S_N u_p + \hat{d} \quad (4.14)$$

Above equation (4.14) the corrected-predicted output response is naturally composed of a forced response (contribution of the current and future control moves) and a free response (the output changes that are predicted if there is no future control moves). The difference between the set point trajectory, r, and the future prediction is

$$r - \hat{y}^c = r - \left[S_{past}\Delta u_{past} + S_N u_p + \hat{d}\right] - S_f\Delta u_f \quad (4.15)$$

$r - \hat{y}^c = E^c$ Is corrected predicted error

$r - \left[S_{past}\Delta u_{past} + S_N u_p + \hat{d}\right] = E$ Is unforced error (if no current and future control moves?)

Above equation (4.15) can be write as

$$E^c = E - S_f\Delta u_f \quad (4.16)$$

Where the future predicted errors are composed of free response (E) and forced response ($-S_f\Delta u_f$) contributions.

The least square objective function equation (1) can be write as

$$\varphi = Q\sum_{i=1}^{P}({e^c}_{k+i})^2 + R\sum_{i=0}^{M-1}(\Delta u_{k+i})^2 \quad (4.17)$$

Note that the quadratic terms can written in matrix-vector as

$$Q\sum_{i=1}^{P}(e^c{}_{k+i})^2 = Q[e^c{}_{k+1}e^c{}_{k+2}\cdots\cdots e^c{}_{k+P}]\begin{bmatrix} e^c{}_{k+1} \\ e^c{}_{k+2} \\ \vdots \\ \vdots \\ e^c{}_{k+P} \end{bmatrix} \quad (4.18)$$

$$Q\sum_{i=1}^{P}(e^c{}_{k+i})^2 = (E^c)^T QE^c \quad (4.19)$$

$$R\sum_{i=0}^{M-1}(\Delta u_{k+i})^2 = R[\Delta u_k \Delta u_{k+1}\cdots\Delta u_{k+M-1}]\begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \vdots \\ \Delta u_{k+M+1} \end{bmatrix} \quad (4.20)$$

$$R\sum_{i=0}^{M-1}(\Delta u_{k+i})^2 = \Delta u^T{}_f R\Delta u_f \quad (4.21)$$

Therefore objective function can be written with the half of equation (4.19) and (4.21)

$$\varphi = (E^c)^T QE^c + \Delta u^T{}_f R\Delta u_f \quad (4.22)$$

From equation (4.16) and (4.22) we can write as

$$\varphi = (E - S_f\Delta u_f)^T Q\left(E - S_f\Delta u_f\right) + \Delta u^T{}_f R\Delta u_f \quad (4.23)$$

For minimization of objective function differentiate equation (4.23) with respect to control move vector then.

$$\frac{\partial\varphi}{\partial\Delta u_f} = -2S^T{}_f QE + 2\left(S^T{}_f QS_f + R\right)\Delta u_f = 0 \quad (4.24)$$

Δu_f Find from equation (4.24)

$$\Delta u_f = (S^T{}_f QS_f + R)^{-1} S^T{}_f QE \quad (4.25)$$

$K_c = (S^T{}_f QS_f + R)^{-1} S^T{}_f Q$Is called controller gain matrix having dimension $rM \times mP$

Where *r* and *m* are number of output and input respectively.

Note that the current and future control move vector (Δu_f) is proportional to the unforced error vector(E). That is, a controller gain matrix,K_c multiplies the unforced error vector (the future errors that would occur if there were no control move changes implemented)

Because only the current control move is actually implemented, we use the first row of the K_c matrix

$$\Delta u_k = K_{c1}E \quad (4.26)$$

K_{c1} Having dimension $r \times mP$In case of SISO dimension of $K_c$matrix is $M \times P$ and K_{c1} matrix is$1 \times P$.

4.6 MPC with in equality Constraints

Inequality constraints on input and output variables are important characteristics for MPC applications. In fact, inequality constraints were a primary motivation for the early development of MPC. Input constraints occur as a result of physical limitations on plant equipment such as pumps, control valves, and heat exchangers, and heat exchangers. For example, a manipulated flow rate might have a lower limit of zeros and an upper limit determined by the pump, control valve, and piping characteristics. The dynamics associated with large control valves impose rate-of-change limits on manipulated flow rates.

Constraints on output variables are a key component of the plant operating strategy. For example, a common distillation column control objective is to maximize the production rate while satisfying constraints on product quality and avoiding undesirable operating regimes such as flooding or weeping.

Inequality constraints can be included in the control calculations in many different ways [9] [6]. It is convenient to make a distinction between hard constraints and soft constraints. As the name implies, a hard constraint cannot be violated at any time. By the cost function, as described below. This approach allows small constraint violations to be tolerated for short periods of time. Key features of the QDMC algorithm is

1. Linear step response for the plant.
2. Quadratic performance objective over a finite prediction horizon.
3. Future plant output behavior specified by trying to follow the set point as closely as possible subject to a move suppression term.
4. Optimal inputs computed as the solution to a quadratic program.

The input constraints can be of the following form

$u_{min} \leq u_{k+i} \leq u_{max}$(4.27)

This is suitable for minimum and maximum flow rates, for example. In addition, velocity constraints that limit the magnitude of the control moves at each sample time have the following form

$\Delta u_{min} \leq \Delta u_{k+i} \leq \Delta u_{max}$(4.28)

Where ordinary,$\Delta u_{min} = -\Delta u_{max}$. To use a standard quadratic program (QP), the constraints in (4.27) need to be written in terms of the control moves, Δu_{k+i} since the previously implemented control action Δu_{k-1} is known, we can write

$$u_k = u_{k-1} + \Delta u_k$$

$u_{k+1} = u_{k-1} + \Delta u_k + \Delta u_{k+1}$(4.29)

The manipulated input constraints are enforced over the control horizon of Msteps, (4.27) and (4.29) yield

$$\begin{bmatrix} u_{min} \\ u_{min} \\ \vdots \\ \vdots \\ u_{min} \end{bmatrix} \le \begin{bmatrix} u_{k-1} \\ u_{k-1} \\ \vdots \\ \vdots \\ u_{k-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \vdots \\ \Delta u_{k+M-1} \end{bmatrix} \le \begin{bmatrix} u_{max} \\ u_{max} \\ \vdots \\ \vdots \\ u_{max} \end{bmatrix} \quad (4.30)$$

Most standard QP codes use a “one-sided” form

$$\begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \vdots \\ \Delta u_{k+M-1} \end{bmatrix} \ge \begin{bmatrix} u_{min} - u_{k-1} \\ u_{min} - u_{k-1} \\ \vdots \\ \vdots \\ u_{min} - u_{k-1} \end{bmatrix} \quad (4.31a)$$

And

$$-\begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \vdots \\ \Delta u_{k+M-1} \end{bmatrix} \ge \begin{bmatrix} u_{k-1} - u_{max} \\ u_{k-1} - u_{max} \\ \vdots \\ \vdots \\ u_{k-1} - u_{max} \end{bmatrix} \quad (4.31b)$$

This has the form $A\Delta u_f \ge b$

The velocity constraints are implemented as bounds on the control moves

$$\begin{bmatrix} \Delta u_{min} \\ \Delta u_{min} \\ \vdots \\ \vdots \\ \Delta u_{min} \end{bmatrix} \le \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \vdots \\ \Delta u_{k+M-1} \end{bmatrix} \le \begin{bmatrix} \Delta u_{max} \\ \Delta u_{max} \\ \vdots \\ \vdots \\ \Delta u_{max} \end{bmatrix} \quad (4.32)$$

The majority of constrained MPC can be solved based on the input constraints consider above. For completeness, however, we also show constraints on the process outputs can be included.

It may be desirable to force the predicted process outputs to be within a range of minimum and maximum values

$y_{min} \le \hat{y}^c{}_{k+i} \le y_{max}$(4.33)

Above equation (4.14) write in the following form

$\hat{y}^c = S_f \Delta u_f + f$(4.34)

Where$f$, the free response of the corrected-predicted output (if no current and future control moves are made) is

$f = S_{past}\Delta u_{past} + S_N u_P + \hat{d}$(4.35)

So that equation (4.34) can be written as

$y_{min} - f \le \hat{y}^c{}_{k+i} \le y_{max} - f$(4.36)

In term of one side inequalities

$S_f \Delta u_f \ge y_{min} - f$

$-S_f \Delta u_f \ge -y_{max} + f$(4.37)

Expand equation (4.23) we get objective function

$\varphi = -2\Delta u^T{}_f S^T{}_f QE + \Delta u^T{}_f \left(S^T{}_f Q S_f + R\right)\Delta u_f$(4.38)

Equation (4.38) writes in this form

$\varphi = \frac{1}{2}\Delta u^T{}_f H \Delta u_f + c^T \Delta u_f$(4.39)

Where

$H = S^T{}_f Q S_f + R$ And $c^T = \Delta u^T{}_f S^T{}_f E = E^T \Delta u_f S_f$

$A\Delta u_f \ge b$(4.40)

Inequality matrices A and b in equation (4.40) incorporate the matrices in equation (4.31) and (4.35)

4.7Extensions of the basic MPC model formulation

There are several extensions of the basic MPC problem formulation that are important for practical applications.

4.7.1Integrating process

The standard step-response model in equation (4.3) is not appropriate for an integrating process because its step response is unbounded. However, because the output rate of change, $\Delta y(k) = y(k+1) - y(k)$ is bounded, a simple modification eliminates this problem. Replacing $\hat{y}_k$ in equation (4.3)$\Delta\hat{y}_k = \hat{y}_k - \hat{y}_0$ provides an appropriate step-response model for integrating process [19]:

$\Delta\hat{y}_k = \sum_{i=1}^{N-1} S_i \,\Delta u_{k-i} + S_N u_{k-N}$(4.41)

Or equivalently,

$\hat{y}_k = \hat{y}_0 \sum_{i=1}^{N-1} S_i \,\Delta u_{k-i} + S_N u_{k-N}$(4.42)

But the bias correction approach is not valid for integrating process, several model fictions are available [6].

4.7.2Known disturbance

If a disturbance variable is known or can be measured, it can be include in the step-response model. Let d denote a measured disturbance and S_i^d its step-response coefficients of known disturbance. Then the standard step-response model in equation (4.3) can be modified by adding a disturbance term,

$$\hat{y}_k = \sum_{i=1}^{N-1} S_i \, \Delta u_{k-i} + S_N u_{k-N} + \sum_{i=1}^{N_d-1} S^d{}_i \Delta d_{k-i} + S^d{}_N d_{k-N_d} \quad (4.43)$$

Where N_d is the number of step-response coefficient for the disturbance variable (in general$N_d \neq N$).

4.7.3Impulse response model

Model predictive control strategies can be based on either impulse-response models or step response models because the two models are closely related. The derivations of the prediction equations and control laws for impulse-response models are analogous to those for the step-response models [9] [10].

4.8Predictions for MIMO models

The previous analysis for SISO systems can be generalized to MIMO systems by using the Principle of Superposition. For simplicity, we first consider a process control problem with two outputs, y_1 and y_2, and two inputs, u_1 and u_2. The predictive model consists of four individual step-response models, one for each input-output pairs [4].

$$\hat{y}_{1k} = \sum_{i=1}^{N-1} S_{11,i} \, \Delta u_{1k-i} + S_{11,N} u_{1k-N} + \sum_{i=1}^{N-1} S_{12,i} \, \Delta u_{2k-i} + S_{12,N} u_{2k-N} \quad (4.44)$$

$$\hat{y}_{2k} = \sum_{i=1}^{N-1} S_{21,i} \, \Delta u_{1k-i} + S_{21,N} u_{1k-N} + \sum_{i=1}^{N-1} S_{22,i} \, \Delta u_{2k-i} + S_{22,N} u_{2k-N} \quad (4.45)$$

Where $S_{12,i}$ denotes the ith step-response coefficient for the model that relates y_1 and u_2. The other step-response coefficients are defined in an analogous manner. Above MIMO model is a straightforward generalization of the SISO model in equation (4.3). In general, a different model horizon can be specified for each input-output pair. For equation (4.23)can be specified as N_{21} and N_{22}, if y_2 has very different settling times for changes in u_1 and u_2.

Now generalize the analysis to MIMO models with arbitrary numbers of inputs and outputs. Suppose that there are r inputs and m outputs. In typical MPC applications, $r \leq 20$ and $m \leq 40$.

It is convenient to express MIMO step-response models in vector-matrix notation. Let the output vector be $y = [y_1, y_2, ..., y_m]^T$ and the input vector is $u = [u_1, u_2, ..., u_r]^T$ where superscript T denotes the transpose of a vector of matrix. In analogy with the derivation ofequation(10a) for SISO systems, the MIMO model for the corrected predictions can be expressed in dynamic matrix form:

$$\overset{\approx}{y}(k+1) = S\Delta U(k) + \overset{\wedge 0}{Y}(k+1) + \delta[y(k) - \hat{y}(k)] \text{ (4.46)}$$

Where $\overset{\approx}{y}(k+1)$ is the mP - dimensional vector of corrected predictions over the prediction horizon P .

$$\overset{\approx}{y}(k+1) \overset{\Delta}{=} col[\overset{\approx}{y}(k+1), \overset{\approx}{y}(k+2), ..., \overset{\approx}{y}(k+p)] \text{ (4.47)}$$

$\overset{\wedge o}{y}(k+1)$ is the mP -dimensional vector of the predicted unforced responses,

$$\overset{\wedge o}{y}(k+1) \overset{\Delta}{=} col[\overset{\wedge o}{y}(k+1), \overset{\wedge o}{y}(k+2), ..., \overset{\wedge o}{y}(k+p)] \text{ (4.48)}$$

And $\Delta U(k)$ is the rM -dimensional vector of the next M control moves,

$$\Delta U(k) \overset{\Delta}{=} col[\Delta u(k), \Delta u(k+1), ..., \Delta u(k+M-1)] \text{ (4.49)}$$

The $mP \times m$ matrix δ in equation (46) is defined as

$$\delta \overset{\Delta}{=} [I_m I_m .... I_m]^T \; p \text{ Times(4.50)}$$

Where I_m denotes the $m \times m$identity matrix.

The dynamic matrix S is defined as

$$S \overset{\Delta}{=} \begin{bmatrix} S_1 & 0 & .... & 0 \\ S_2 & S_1 & .... & 0 \\ : & : & ::::::::: & : \\ S_M & S_{M-1} & .... & S_1 \\ S_{M+1} & S_M & .... & S_2 \\ : & : & :::::::::: & : \\ S_P & S_{P-1} & .... & S_{P-M+1} \end{bmatrix} \text{(4.51)}$$

$$S_i \overset{\Delta}{=} \begin{bmatrix} S_{11,i} & S_{12,i} & \cdots\cdots\cdots & S_{1r,i} \\ S_{21,i} & S_{22,i} & \cdots\cdots\cdots & S_{2r,i} \\ : & : & ::::::::: & : \\ S_{m1,i} & S_{m2,i} & \cdots\cdots & S_{mr,i} \end{bmatrix} \quad (4.52)$$

Note that dynamic matrix in equation (4.51) for MIMO systems have the same structure as the one for SISO system in equation (4.13). The move weights S_i are the step response coefficients. Mathematically the step response can be defined as the integral of the impulse response; given one model from the other can be easily obtained. Multiple outputs were handled by superposition. By using the step response model one can write predicted future output changes as a linear combination of future input moves. The matrix that ties the two together is the so-called dynamic

CHAPTER-5

DESIGN PARAMETERS

CHAPTER-5

5.1 Selections of design and tuning parameters

Tuning a controller is a direct way to reach its optimum performance. An MPC controller has certain parameters setting to achieve its optimum performance. Those parameters are sampling time (Δt), prediction horizon (P), control horizon (M), model horizon (N), controlled variable weights.

Model Length N:

N is an important factor. It affects the step response coefficients and the disturbance response coefficients. It is related to the sampling period T by the relation that T=N* Δt where Δt is the sampling interval. The lowest value of this sampling period isgenerally limited by computer capacity and computational speed, and N is generally takenbetween20-70.

Prediction Horizon length P:

P, represents the number of samples into the future over which MPC computes the predicted process variable profile and minimizes the prediction error. Increasing P makesthe control more accurate but increases the computation.

Control horizon length M:

M determines the number of the control actions calculated into the future. Small value of makes the controller insensitive of noise. The less M is useful for controlling the stability of the system while larger M results in excessive control action and increases the flexibility, but it may lead to instability.

Error weight matrix Q:

The output weighting matrix Qallow output variables to weight according to their relative importance).The selection of Q determines the corresponding error term in the optimized control law.

Control weight matrix R:

R Allows input variables to be weighted according to their relative importance.Weight assigned to the control moves

5.2Default setting:

(1)Sampling time period and model horizon:

The sampling period Δt and mode horizon N should be $N\Delta t = t_s$. Where t_s is settling time for the open-loop response? This choice ensures that the model reflects the full effect of a change in an input variable the time required to reach steady state. Typically, 30<N<120

(2) Control M and prediction P horizons:

Typically $5 \le M \le 20$ and $N/3 \le M \le N/2$. A different value of M can be specified for each input. The prediction horizon P is often selected to be $P = N + M$.

(3)Weighting matrices,$Q$and R:

The output weighting matrix Q allow output variables to weight according to their relative importance. Thus, a $mP \times mP$ diagonal Qmatrix allows to the output variables to be weighted individually, with the most important variables having the largest weights.

In similar fashion, R allows input variables to be weighted according to their relative importance. This $rM \times rM$ matrix is referred to as the input weighting matrix or the move suppression matrix.

5.3 Non adaptive DMC tuning strategy:

[11][12]

S.N.	SISO model	MIMO model
1.	FOPDT model $\frac{Y(S)}{U(S)} = \frac{k_p e^{-\theta_p s}}{\tau_p s+1}$	FOPDT model $\frac{Y(S)}{U(S)} = \frac{k_{rs} e^{-\theta_{rs} s}}{\tau_{rs} s+1}$($r$=1,2…$R$;s=1,2..S)
2.	T=max($T \leq 0.1\tau_p$ and $T \leq 0.5\theta_p$)	T=Min(Max($0.1\tau_{rs}, 0.5\theta_{rs}$))($r$=1,2..$R$,$s$=1,2..$S$)
3.	P=N=$(5\frac{\tau_p}{T} + \frac{\theta_p}{T} + 1)$	P=N=$Max(5\frac{\tau_{rs}}{T} + \frac{\theta_{rs}}{T} + 1)$(r=1,2..R,s=1,2..S)
4.	M=$(\frac{\tau_p}{T} + \frac{\theta_p}{T} + 1)$	M=$Max(\frac{\tau_{rs}}{T} + \frac{\theta_{rs}}{T} + 1)$ (r=1,2..R,s=1,2..S)
5.	R=$0, M = 1$: $M/500(\frac{3.5\tau_p}{T} + 2 - (M-1)/2)$:M> 1	$R = M/500 \sum_{r=1}^{R}[Q^2{}_r(\frac{\theta_{rs}}{T} + 1)^2\{P - \left(\frac{\theta_{rs}}{T} + 1\right) - \frac{3}{2}\left(\frac{\tau_{rs}}{T}\right) + 2 - (M-1)/2\}]$,s=123,…S

Table5.1 Non adaptive DMC tuning

5.4DMC tuning strategy review:

I prepared a table for DMC tuning, different- author give different-2 approach to find tuning parameter which is shown below table5.1, 5.2, and 5.3[13].

5.4.1 Prediction Horizon:

PREDICTION HORIZON	AUTHOR
$P = [(t_{80} + t_{90})/2]/T_s$	Maurath,P.R.;laub
$P > M + t_d/T_s$	Maurath,P.R.,Mellichamp
$P = M + N$	Cutler,C.R.
$P = \frac{t_{60}}{T_s} + \frac{t_{95}}{T_s} - 1$	Georgiou,A.;Georgakis,C.;Lubyen,W.L.
$P = (5\tau_p + t_d)/T_s$	Hinde,R.F.;Cooper
$P = \max(\frac{5\tau_{rs}}{T_s} + k_{rs})$ $k_{rs} = \frac{\theta_{rs}}{T_s} + 1$	Shridhar,R.;Cooper

Table5.2 prediction horizon

5.4.2 Control Horizon:

CONTROL HORIZON	AUTHOR
$M = t_{60}/T_s$	Georgiou,A.;Georgakis,C.;Lubyen,W.L.
$M = \tau_p/T_s$	Hinde,R.F.;Cooper
$M = \max\left(\frac{\tau_{rs}}{T_s} + k_{rs}\right)$ $k_{rs} = \frac{\theta_{rs}}{T_s} + 1$	Shridhar,R.;Cooper

Table5.3 control horizon

5.4.3 Model Horizon and Sample Time:

MODEL HORIZON	AUTHOR
$N > (\max\,(t_{95,i})/T_s$	Georgiou,A.;Georgakis,C.;Lubyen,W.L.
$N = max\left(\frac{5\tau_{rs}}{T_s} + k_{rs}\right)$ $k_{rs} = \frac{\theta_{rs}}{T_s} + 1$	Shridhar,R.;Cooper

SAMPLE TIME	AUTHOR
$T_S = \min\,[\max\,(0.1\tau_{rs}, 0.5\theta_{rs})]$	Shridhar,R.;Cooper

Table5.4 model horizon

Where

k_{rs} =FOPDT Model gain for R outputs and S inputs

M =Control horizon

N =model horizon

P =Prediction horizon. T_s =sampling time

τ_p =FOPDT Process time constant

τ_{rs} =FOPDT Process time constant (s) for R outputs and S Inputs

t_d =Process delay time

θ_{rs}=FOPDT Process delay time constant(s) for R outputs and S inputs

After study of table 5.3 we can clearly see that rest of R. Sridhar and D. Cooper design parameter given for SISO model, only R. Sridhar andD. Cooper.

5.5Conversion of (SOPDT) to (FOPDT):

All design parameter given for first order plus dead time (FOPDT), if process has second order plus dead time (SOPDT) then that time we have to change (SOPDT) to (FOPDT) blow given the procedure.

First- order plus dead-time (FOPDT) Model

$G(S) = Ke^{-t_0 s}/(\tau s + 1)$(5.1)

Second –order plus dead-time (SOPDT) Model

$G(S) = Ke^{-ts}/(\tau_1 s + 1)(\tau_2 s + 1)$(5.2)

$K =$ The process steady-state gain

$t, t_0 =$ The effective process dead time

$\tau_1, \tau_2, \tau =$ The effective process time constants

For $\tau_1 = \tau_2 t_0 = 0.505\tau_1 + t\tau = 1.641\tau_1$

For $\tau_1 \ll \tau_2 t_0 = \tau_2 + t\tau = \tau_1$

The above conversion have done with the help of example 10 (page no 222) of principles and practice of automatic process control (CARLOS A. SMITH, ARMANDO)

CHAPTER- 6

IMPEMENTATION OF DISTILLATION COLUMN

CHAPTER 6

In this chapter first describe the effect of tuning parameters on SISO models, model predictive controller use to control the MIMO distillation column process ($2 \times 2, 3 \times 3$ and4×4). And the effect of tuning parameters on step response model of a water heater.

6.1 Effect of design parameters:

Here we see the effect design parameter on single input single output model like control horizon, prediction horizon, model horizon, sampling time, input weight output weight.

A SISO process has the transfer function.

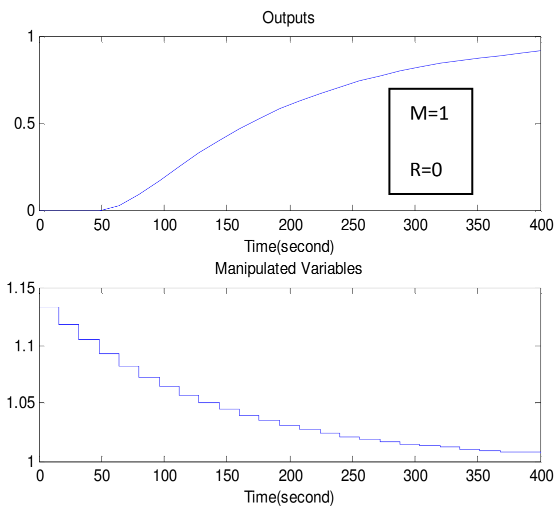
$$\frac{Y(S)}{U(S)} = \frac{e^{-50s}}{(150S+1)(25S+1)} \quad [11] \tag{6.1}$$

Above transfer function is second order plus dead time (SOPDT), for find design parameter we have to change in first order plus dead time (FOPDT);

$$\frac{Y(S)}{U(S)} = \frac{e^{-70s}}{(170S+1)} \tag{6.2}$$

6.1.1Effect of move suppression coefficient (input weight):

For analysis move suppression coefficient sampling time taken T=16, prediction horizon=54, and model horizon=54. Figure 6.1 illustrate the response to a step change in set point when the control horizon is 1 and no move suppression is used. Note that for M =1, the set point step response is sluggish. Figure 6.2-6.3 shows the impact of R on performance for a control horizon of M = 4. Figure 6.2 demonstrates that, with M>1, the without move suppression results in dramatically aggressive control effort and significantly under damped measured output response. Figure 6.3 show that an intermediate response can be achieved by an appropriate choice R=0.14. Figure 6.4 show that a large move suppression coefficient R=4 results in a slower response. Further increase R can lead to an undesirable sluggish response for most application.Consequently, this study shows that the choice of R is critical to the performance achieved by DMC.



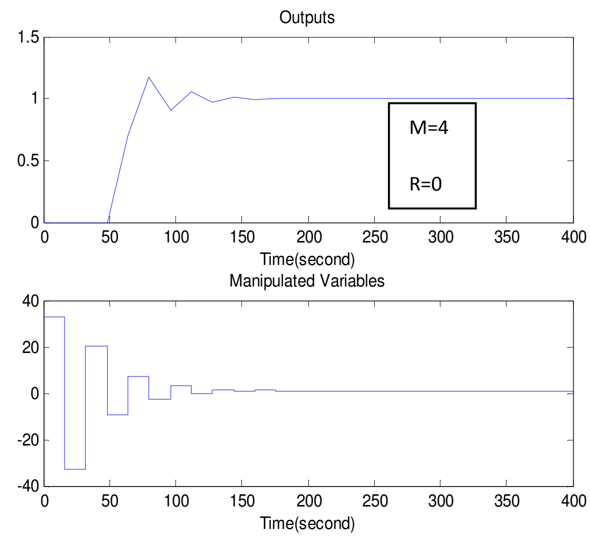
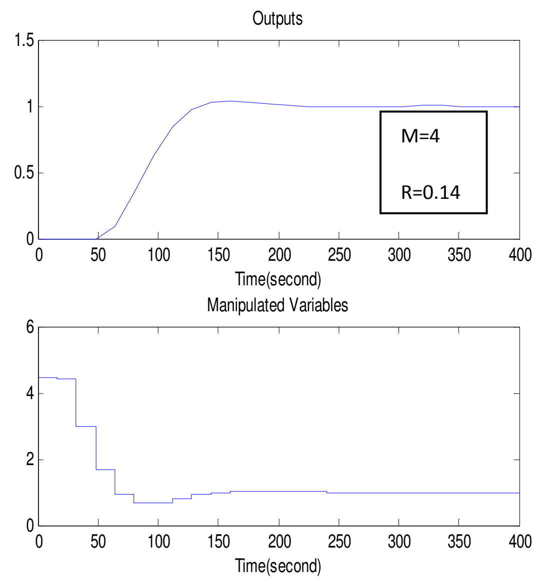


Figure 6.1 output and manipulated variable at $M = 1, R = 0$Figure 6.2 output and manipulated variable at $M = 4, R = 0$



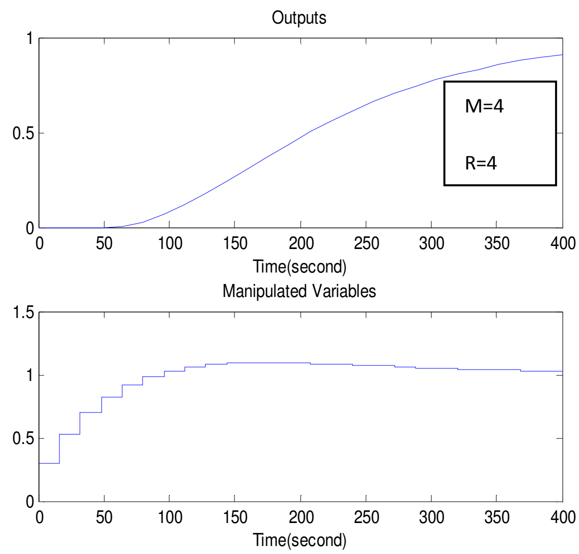


Figure 6.3 output and manipulated variable at $M = 4, R = 0.14$Figure 6.4 output and manipulated variable at $M = 4, R = 4$

6.1.2 Effect of sampling time, prediction horizon:

Figure 6.5 to 6.10 demonstrates the interdependence of prediction horizon, *P*, and sample time, *T*. For different choice of *P* and *T* while maintaining the control horizon *M*=4, and move suppression coefficient, *R*=0.14. At large sampling time *T*=24, prediction horizon *P* increase from 9 to 16 in this case response is almost same.

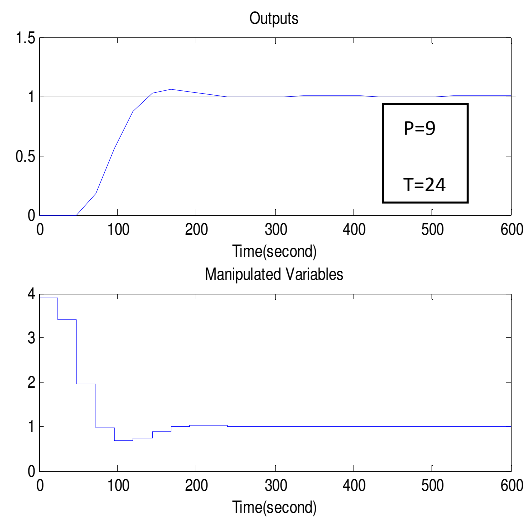


Figure 6.5 output and manipulated variable at $P = 9, T = 24$

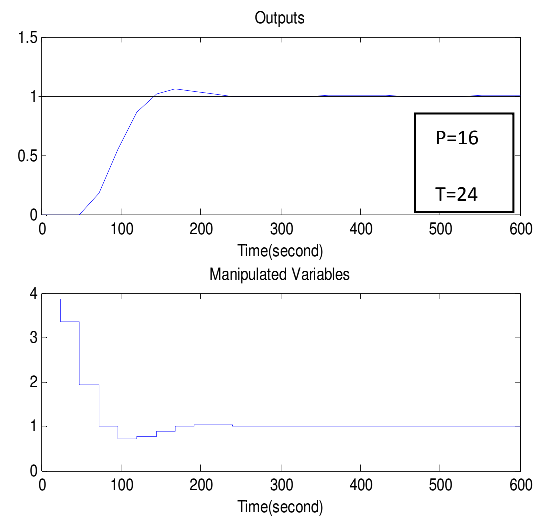


Figure 6.6 output and manipulated variable at $P = 16$

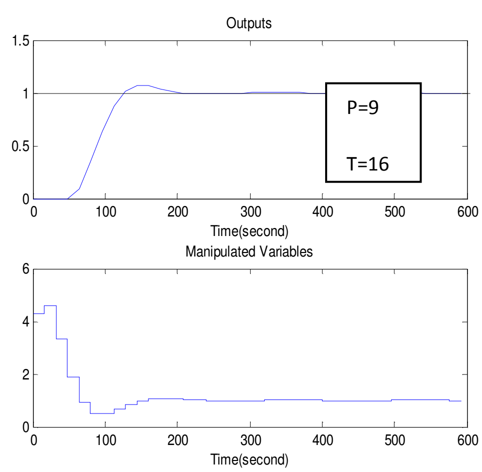


Figure 6.7output and manipulated variable at $P = 9, T = 16$

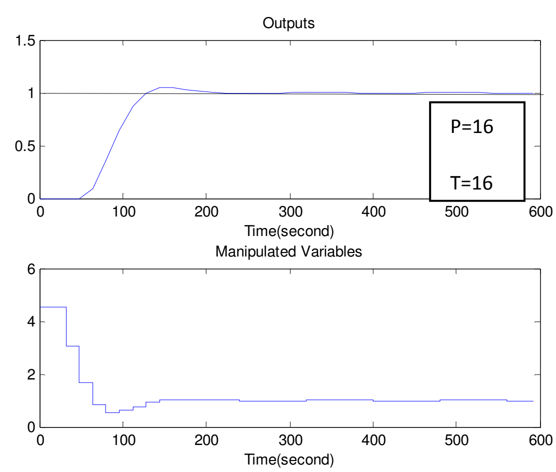
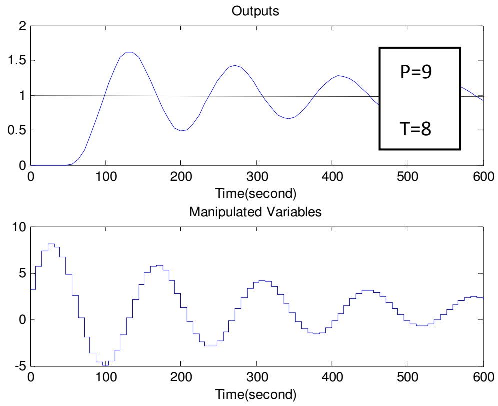


Figure 6.8 output and manipulated variable at $P = 16, T = 16$



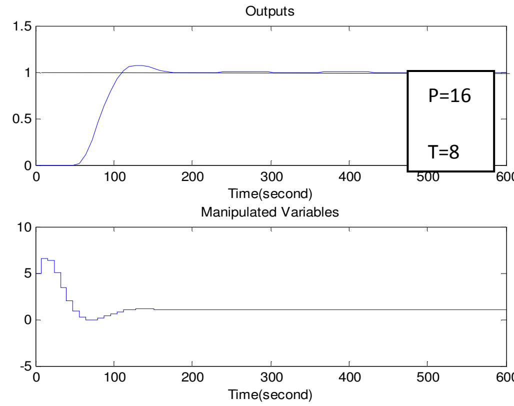
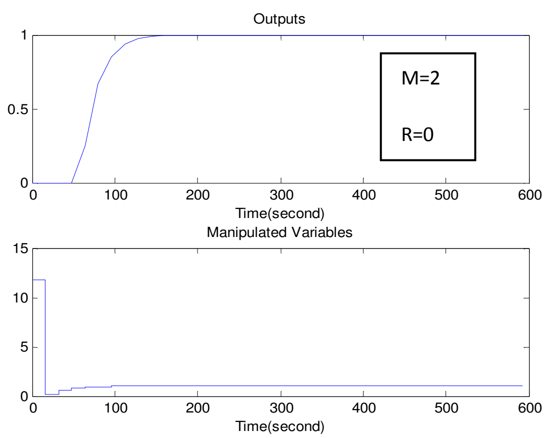


Figure 6.9output and manipulated variable at $P = 9, T = 16$Figure 6.10output and manipulated variable at $P = 16, T = 8$

$\frac{T}{\tau_p} = 0.15$ Is used to find the sampling time Where τ_p is time constant Figure6.5, 6.6 and 6.9 illustrate that by decreasing the sampling time for a constant prediction horizon (P=9) the output response becomes increasingly under damped. Above all response show that interrelation of P and T. It is clear that the choice of prediction horizon, P cannot be made independent of sample time.

6.1.3 Effect of control horizon:



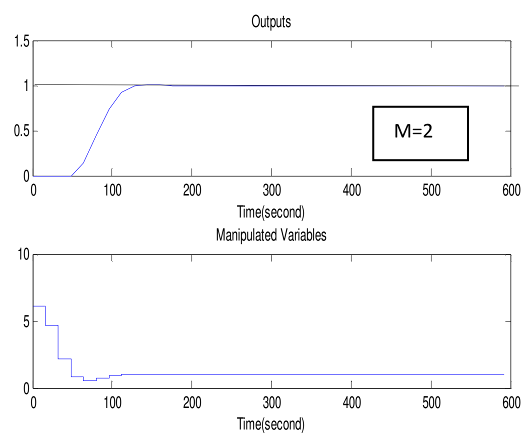
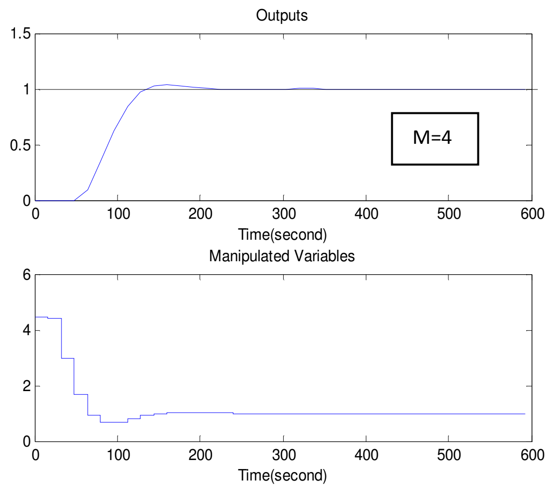


Figure 6.11output and manipulated variable at $M = 2, R = 0$Figure 6.12output and manipulated variable at $M = 2, R = 0.14$



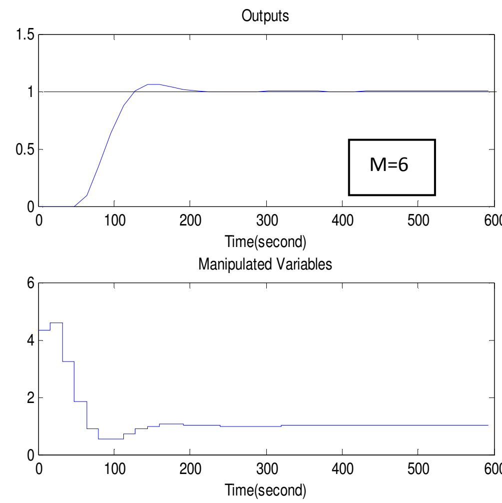


Figure 6.13output and manipulated variable at $M = 4, R = 0.14$Figure 6.14output and manipulated variable at $M = 6, R = 0.14$

Figure 6.11 to 6.14 illustrates the effect of control horizon, *M*, for fixed *P*=54, sampling time 2, and *R*=0.14. Figure 6.12 to 6.14 show that the increasing the control horizon from 2 to 6 does not a alter performance significantly. Noticeable effect is a slight increase in over shoot for a larger control horizon. It indicates stability considerations also restrict the choice of control horizon. For above discussion we found tuning parameter from table 5.1.

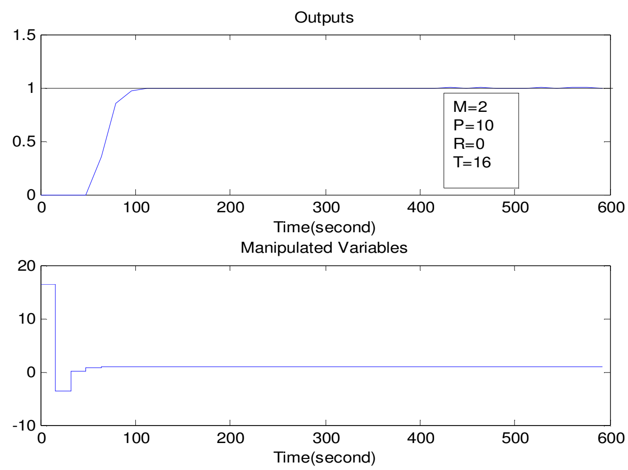


Figure 6.15 output response using tuning default

Figure 6.3 and 6.15 illustrate the effect default tuning, with appropriate choice of *M*=2 and *P*=10 without suppression coefficient minimize the under damped.

6.2 Tuning strategy for higher order process:

$$\frac{Y(S)}{U(S)} = \frac{(1-50s)e^{-10s}}{(100S+)^2}\ [11] \qquad (6.3)$$

Above transfer function is second order plus dead time (SOPDT), for find design parameter we have to change in first order plus dead time (FOPDT);

$$\frac{Y(S)}{U(S)} = \frac{e^{-105s}}{(163S+)} (6.4)$$

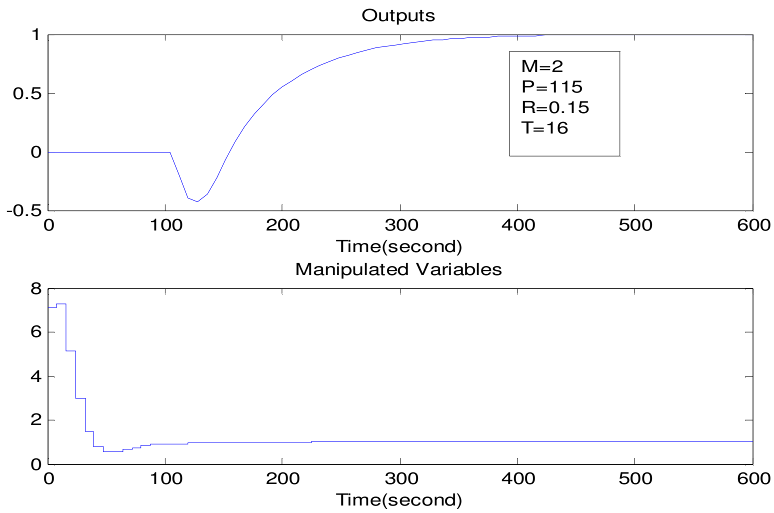


Figure 6.16 responses using tuning parameter

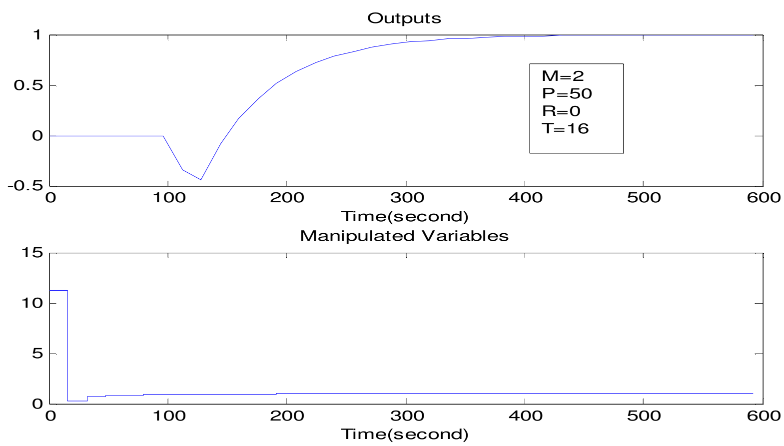


Figure 6.17 responses using tuning parameter

Fig 6.16 and fig 6.17are almost same but it gives the idea of design parameters affected by M, P, T, and R

6.32 × 2 process distillation column:

(1) Wood and Berry 2 × 2 process.

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7S+1} & \frac{-18.9e^{-3s}}{21.0S+1} \\ \frac{6.6e^{-7s}}{10.9S+1} & \frac{-19.4e^{-3s}}{14.4S+1} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} + \begin{bmatrix} \frac{3.8e^{-8.1s}}{14.9s+1} \\ \frac{4.9e^{-3.4s}}{13.2s+1} \end{bmatrix} F(s) \text{ [14]} \tag{6.5}$$

Above equation (6.5) is the model of distillation column it is used to separate methanol and water. Where $X_D(s)$ represents the mole fraction of methanol in distillate, $X_B(s)$ the mole fraction of methanol in bottom are the control variable, manipulated variables $R(s)$ and $S(s)$ are reflux flow rate and steam flow rate respectively and feed flow rate.

Design parameters from table 5.1find out M=15, P=75,T=1.67setting other parameters defaults.

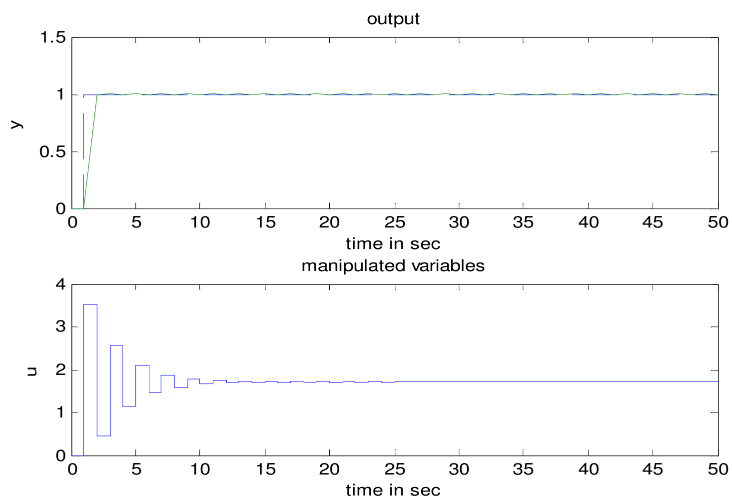


Figure 6.18 response of Wood Berry without Disturbance

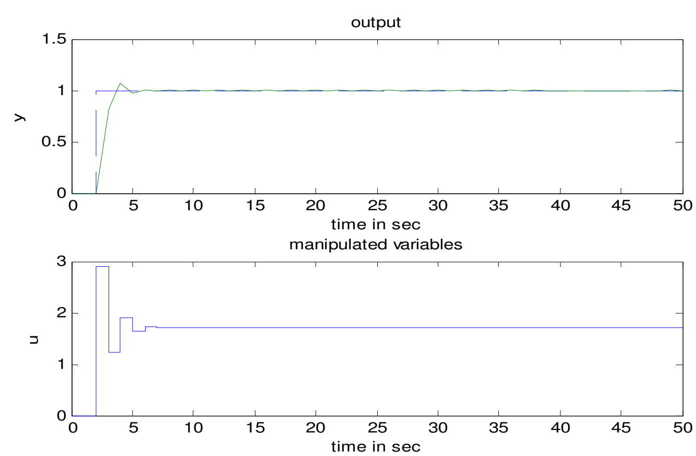


Figure 6.19 response of Wood Berry with Disturbance

Above figure6.18, 6.19 is response of wood and berry distillation column model, figure6.19 indicate that when disturbance applied peak overshoot and settling time increased due to reason of disturbance.

But in both of case manipulated variable ringing so now try to reduce ringing with the change of design parameters, for reduce ringing take design parameter *M*=2, *P*=10, and *T*=2.

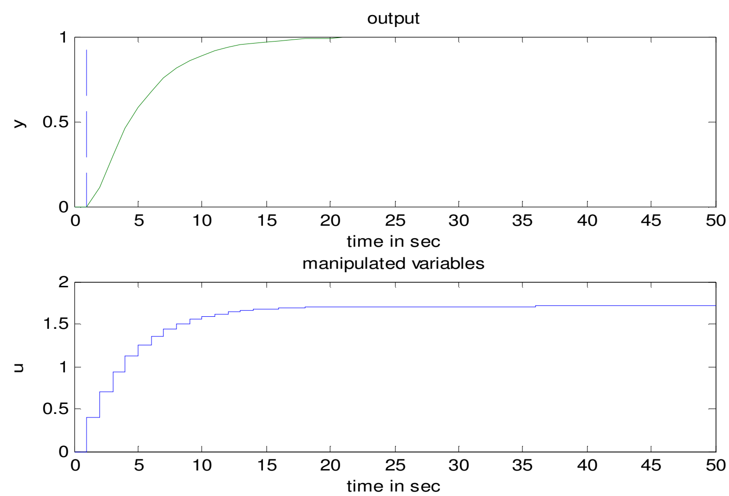


Figure 6.20 response using design parameter default without disturbance

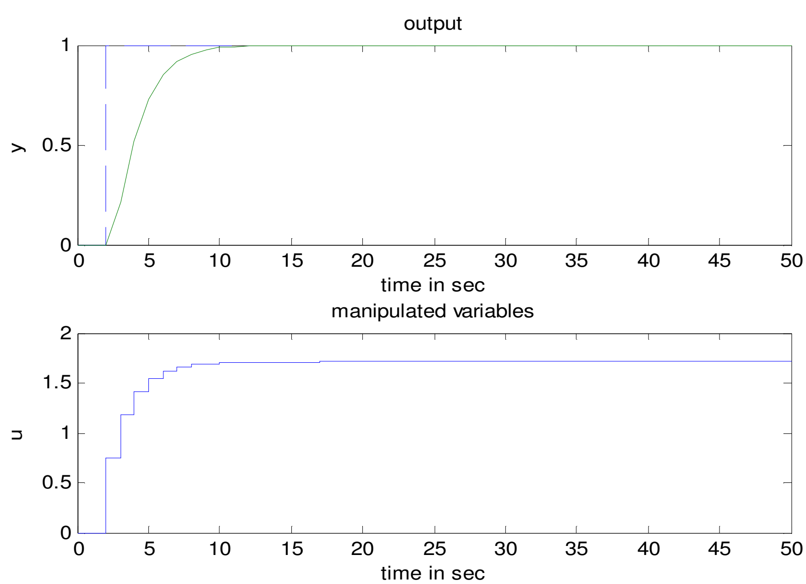


Figure 6.21 response using design parameter default with disturbance

In above figure 6.20 and 6.21 manipulated variables ringing less than figure 6.18 and 6.19. It indicates that with the change of design parameters it is possible to reduce ringing of manipulated variable.

6.4 3 × 3 Process Distillation column.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} \frac{1.986e^{-0.71s}}{(6.7S+1)} & \frac{-5.2e^{-60s}}{(400S+1)} & \frac{-5.984e^{-2.24s}}{(14.29S+1)} \\ \frac{-0.0204e^{-0.59s}}{(7.14S+1)^2} & \frac{-0.33e^{-0.68s}}{(2.38S+1)^2} & \frac{-0.012e^{-0.42s}}{(1.43S+1)} \\ \frac{-0.374e^{-7.75s}}{(22.22S+1)} & \frac{11.3e^{-3.79s}}{(21.7S+1)^2} & \frac{9.811e^{-1.59s}}{(11.36S+1)} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \tag{6.6}$$

Above equation (6.6) tyreus studied a side stream column seperation a ternary mixture, where controlled and manipulated variables are Y_1(toluene impurity in distillate), Y_2(benzene impurity in the side stream),Y_3(toluene impurity in the bottom), u_1(reflux ratio), u_2(side stream flow rate) u_3(reboil duty).

When find the design parameters from table 5.1 than M=339, P= N=1111, T=1.8

Here large value of tuning parameter because of g12 transfer function.

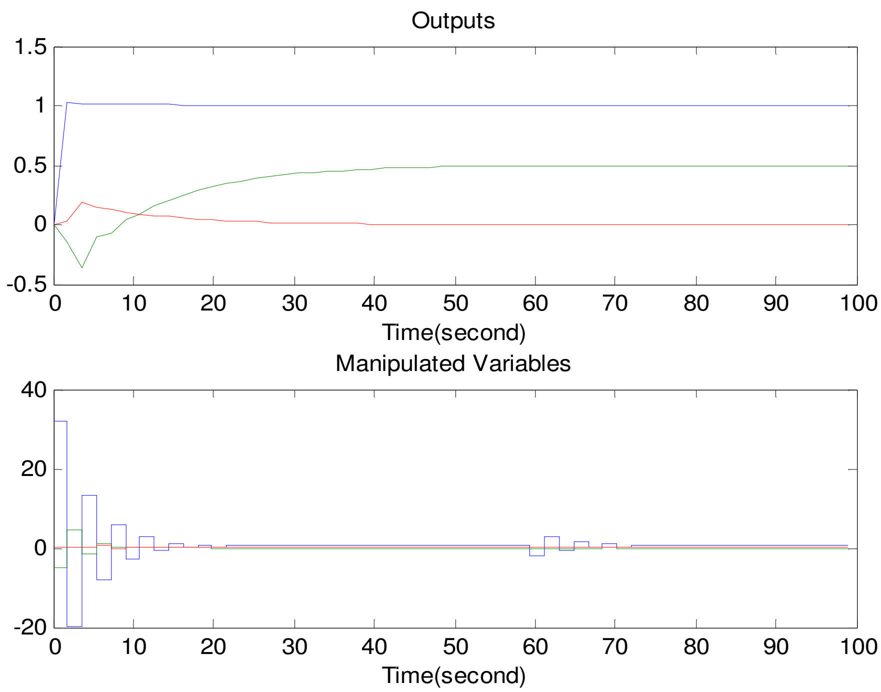


Figure 6.22 response using DMC tuning table5.1

Response come but take more simulation time at above parameters, now try on default setting T=1.8, M=2, P=10.

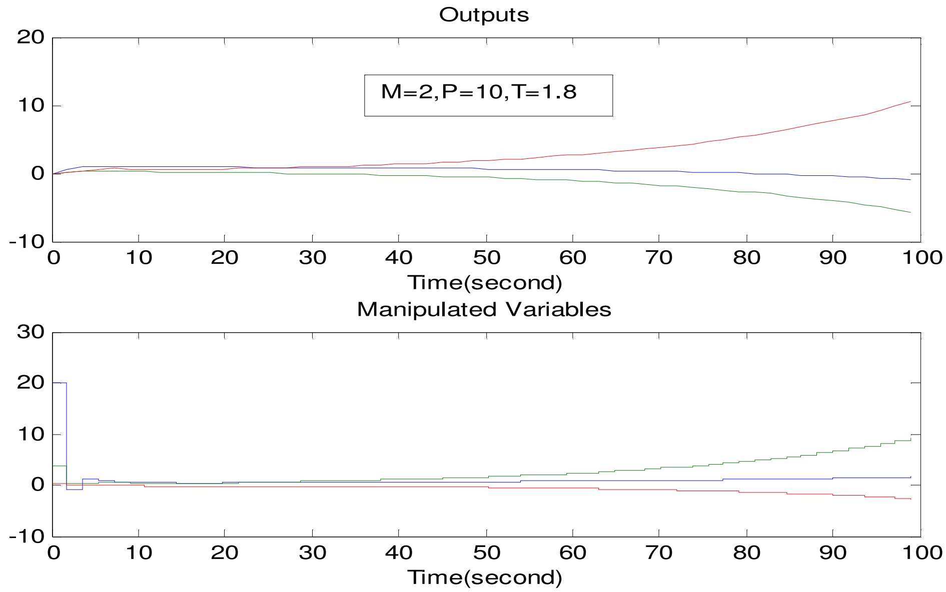


Figure6.23 response using default setting.

We can clearly see that above performance is not stable response, so now design parameter taken M=10,P=20,T=1.8

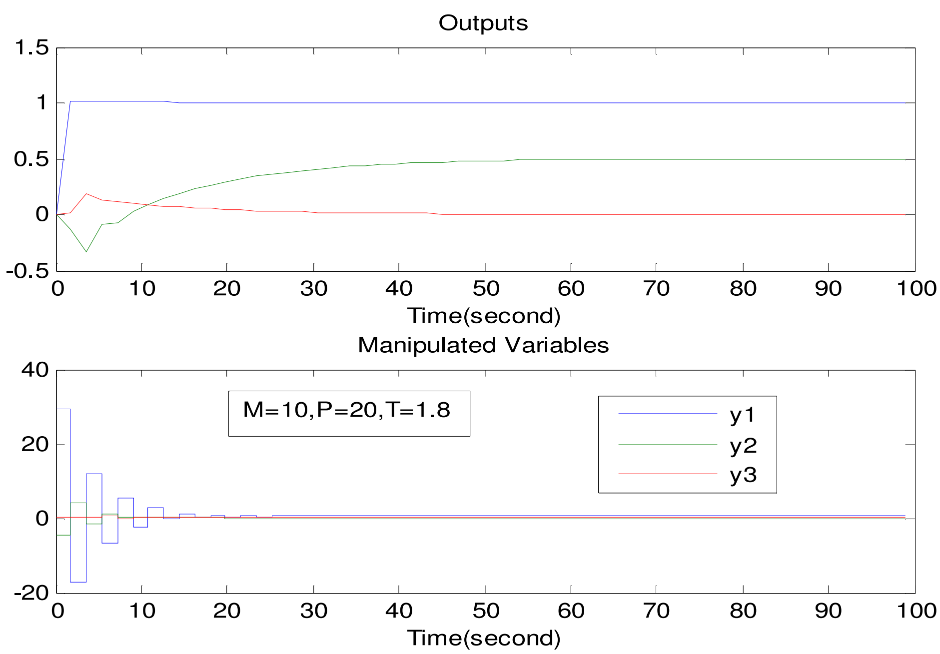


Figure 6.24 stable response of tyerus another value

6.5Doukas and Luyben 4×4 Process:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} \frac{-11.3e^{-3.79s}}{(21.74S+1)(21.74S+1)} & \frac{0.3746e^{-7.75s}}{(31.6S+1)(22.2s+1)} & \frac{-9.811e^{-1.59s}}{(11.36S+1)} & \frac{-2.3711e^{-27.33s}}{(33.3S+1)} \\ \frac{-5.24e^{-60s}}{(400S+1)} & \frac{-1.986e^{-0.71s}}{(66.7S+1)} & \frac{-5.984e^{-2.24s}}{(14.29S+1)} & \frac{0.422e^{-8.72s}}{(250S+1)^2} \\ \frac{-0.33e^{-0.68s}}{(2.38S+1)(2.38S+1)} & \frac{0.0204e^{-0.59s}}{(7.14S+1)(7.14S+1)} & \frac{2.38e^{-0.42s}}{(1.43S+1)(1.43S+1)} & 0.513e^{-s} \\ \frac{-4.488e^{-0.52s}}{(11.11S+1)} & \frac{-0.176e^{-0.48s}}{(6.90S+1)(6.90S+1)} & \frac{-11.67e^{-1.191s}}{(12.19S+1)} & 15.54e^{-s} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \quad (6.7)$$

The above 4×4 process is presented by Doukas and Luyben. They studied the dynamic of a distillation column producing a liquid side stream product. The controlled and manipulated variables are Y_1(toluene impurity in the bottom), Y_2(toluene impurity in the distillate),Y_3(benzene impurity in the side stream), andY_4(xylene impurity in the side stream); u_1(side stream flow rate),u_2(reflux ration),u_3(reboil duty), and u_4(side draw location).

Above process has eight FOPDTs, six SOPDTs, and two dead times. The six SOPDT models are changed to FOPDTs model in order to apply DMC tuning, DMC tuning find out from table (5.1) is M=1087,T=0.5 and P=4370. The huge DMC parameters are caused by the transfer function g24.MPC controller gives an error statement using DMC tuning from table (5.1).

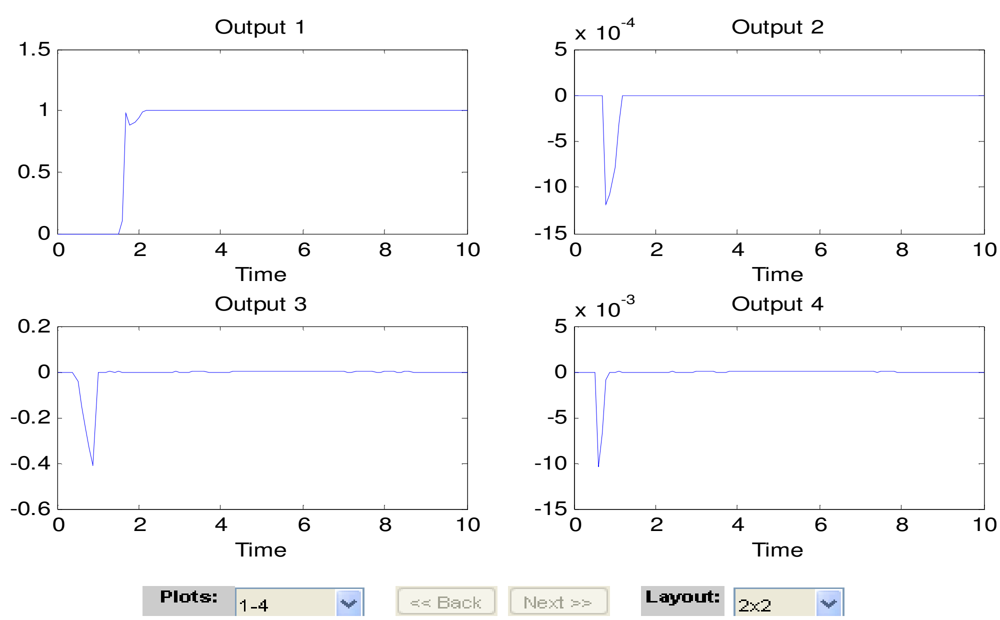


Figure 6.25 Doukas and Luyben output at default

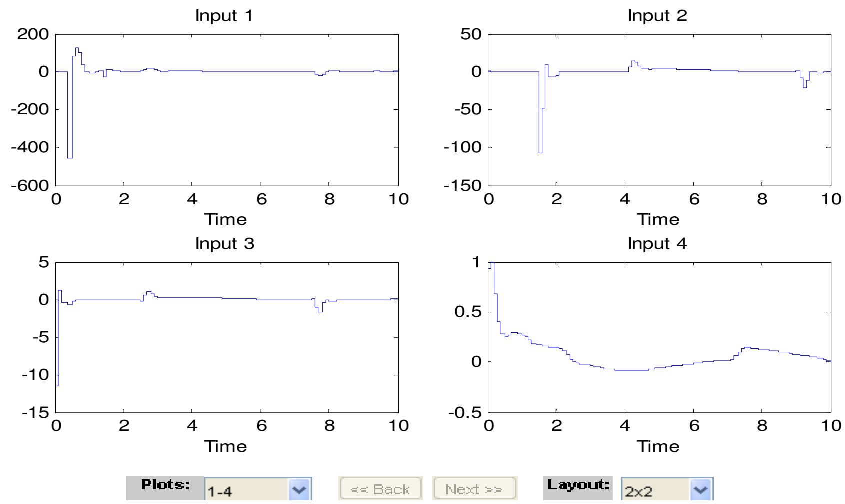


Figure 6.26 Doukas and Luyben manipulated variablesat default

Above MPC controller output at come at default setting where T=0.1, M=5 P=*10,* N=60

6.7 Constraints SISO Process.

Y=$\frac{5.72e^{-14s}}{60S+1}u(s) + \frac{1.52e^{-15s}}{25S+1}d(s)$ (6.8)

For above SISO process taking tuning parameters default M=5, P=10, T=1

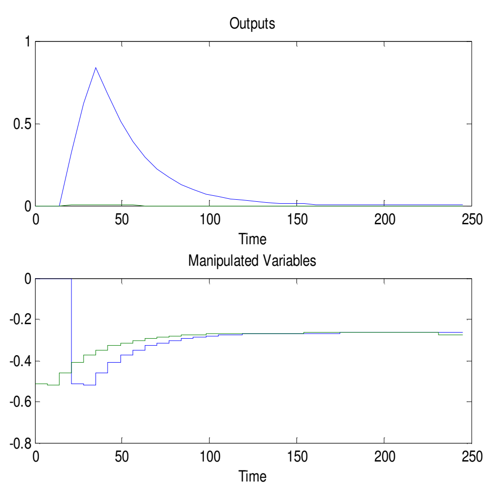


Fig6.27 response unconstraint

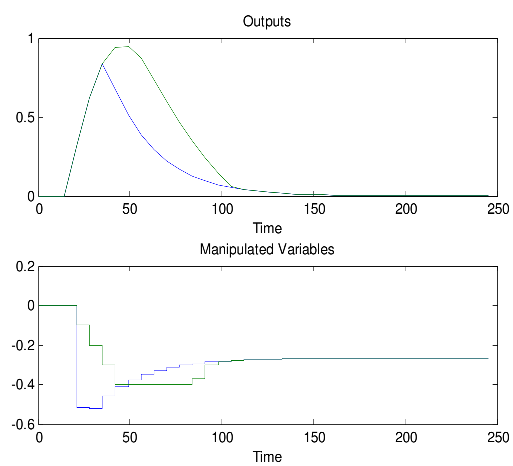


Fig 6.28 responses after constraint

In figure 6.28 constraints impose as lower limit -0.40 and upper limit infinity.

CHAPTER-7

EFFECT OF DMC TUNNING PARAMETERS ON STEP RESPONSE MODEL OF WATER HEATER

7 Effect of DMC tunning parameters on Step response model of a water heater [17],[22]

p.sr=[0;0;0.271;0.498;0.687;0.845;0.977;1.087;1.179;1.256;.....

1.320;1.374;1.419;1.456;1.487;1.513;1.535;1.553;1.565;1.581;....

1.592;1.600;1.608;1.614;1.619;1.632;1.627;1.630;1.633;1.635];

7.1 Effect of control weight on step response model of water heater

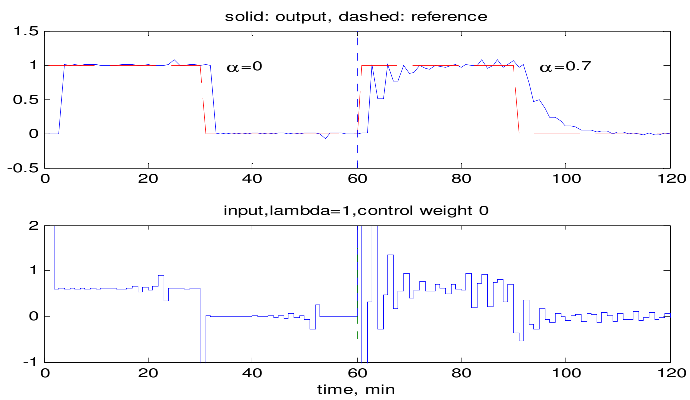


Fig:7. 1 Response for control weight 0

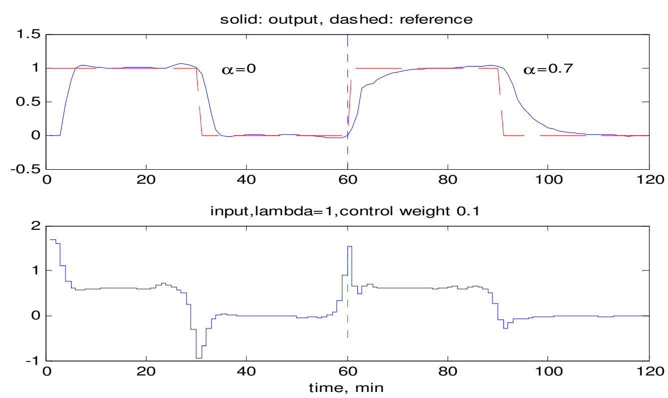


Fig7. 2 Response for control weight 0.1

From Fig7.1 ,Fig7. 2 we can observe that the ringing decreses when the control weight increses.with out control weight large distartions take place, In output so many peak over shoots happened.

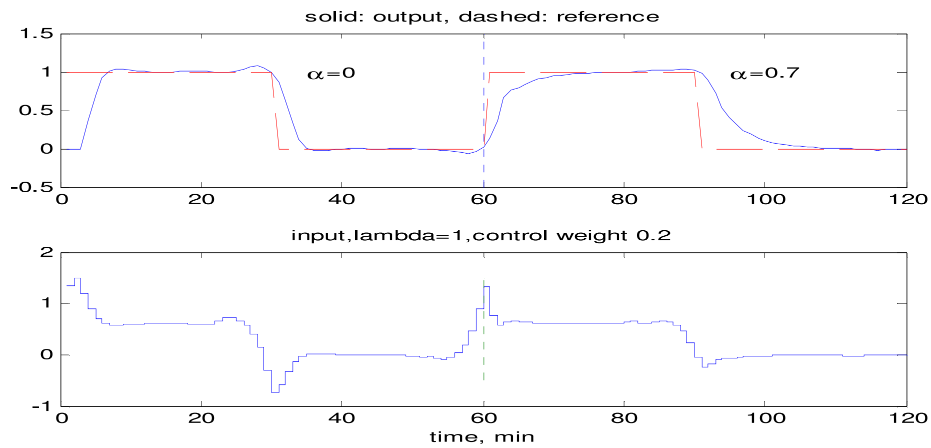


Fig7. 3 Response for control weight 0.2

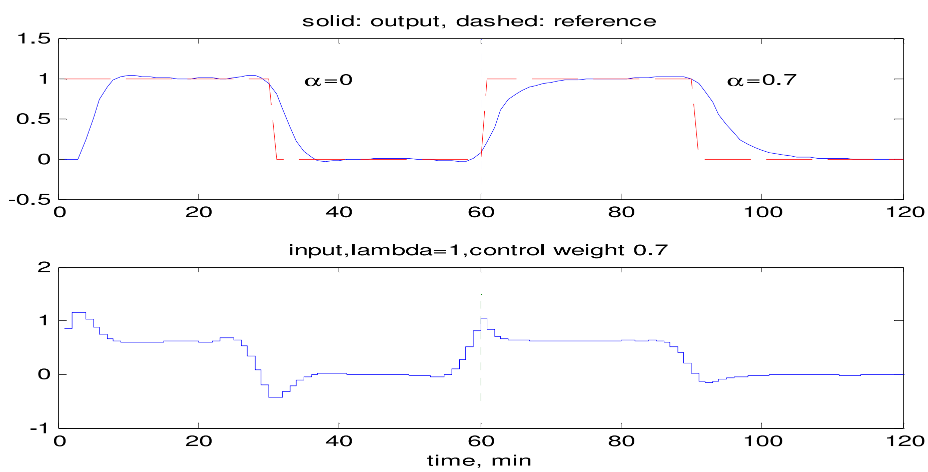


Fig 7.4Response forcontrol weight 0.7

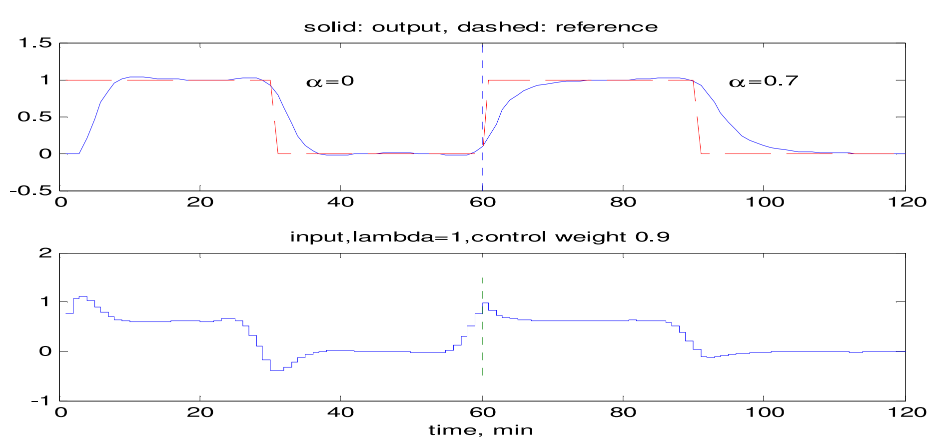


Fig7. 5Response forcontrol weight 0.9

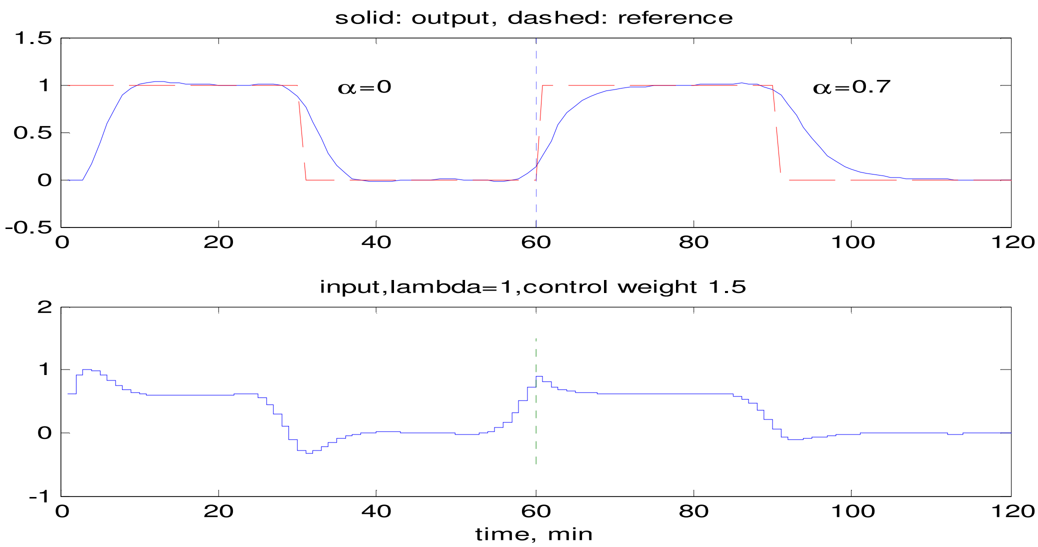


Fig 7.6Response forcontrol weight 1.5

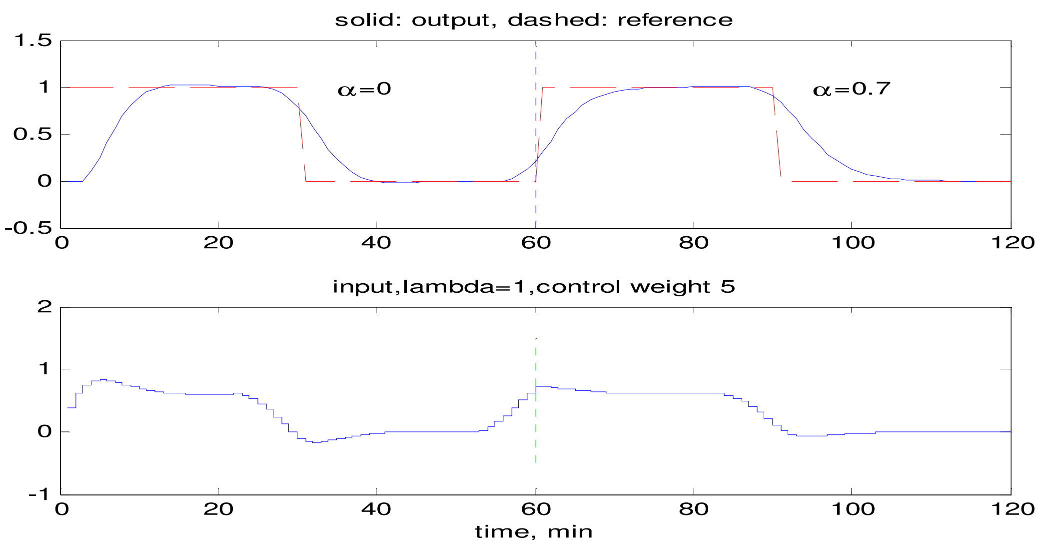


Fig 7.7Response forcontrol weight 5

From Fig7.3 to Fig7.7 we can observed that the ringing decreases when the control weight increases and also peak overshoot decreases, got a stable response.

7.2 Effect of moving horizon (m)&prediction horizon(p) on step response model of water heater

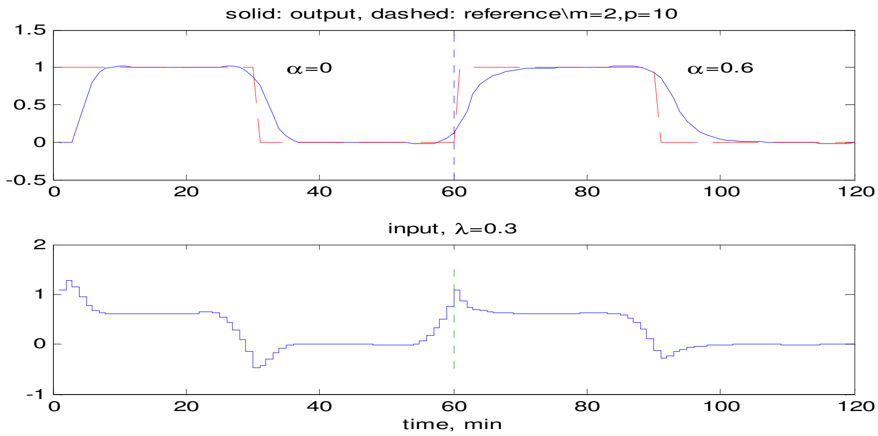


Fig 7.8Response for m=2,p=10

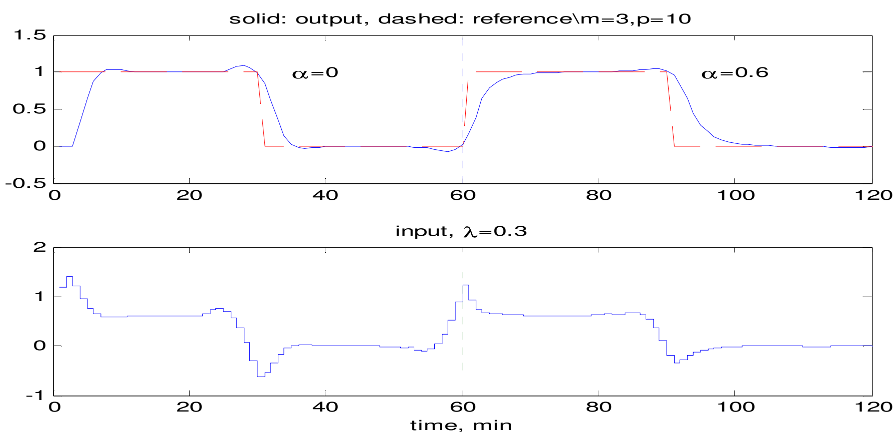


Fig 7.9 Response for m=3,p=10

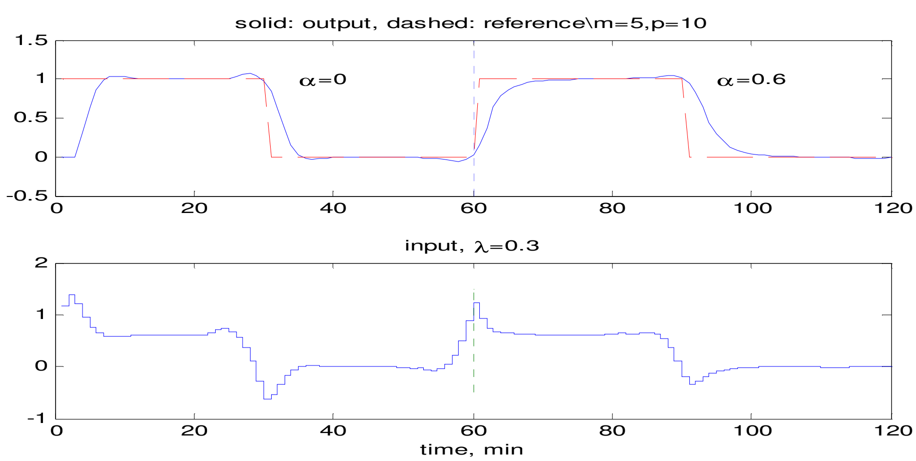


Fig 7.10 Response for m=5,p=10

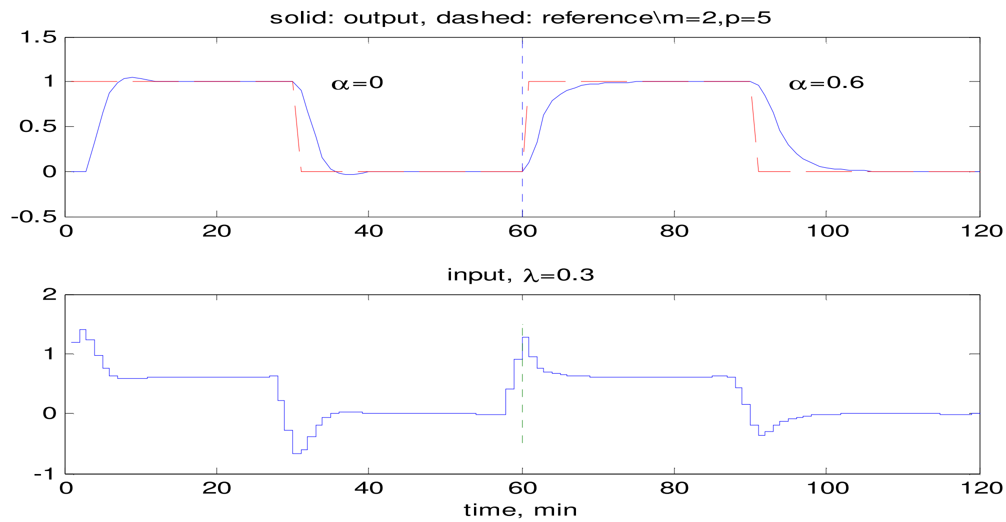


Fig 7.11 Response for m=2,p=5

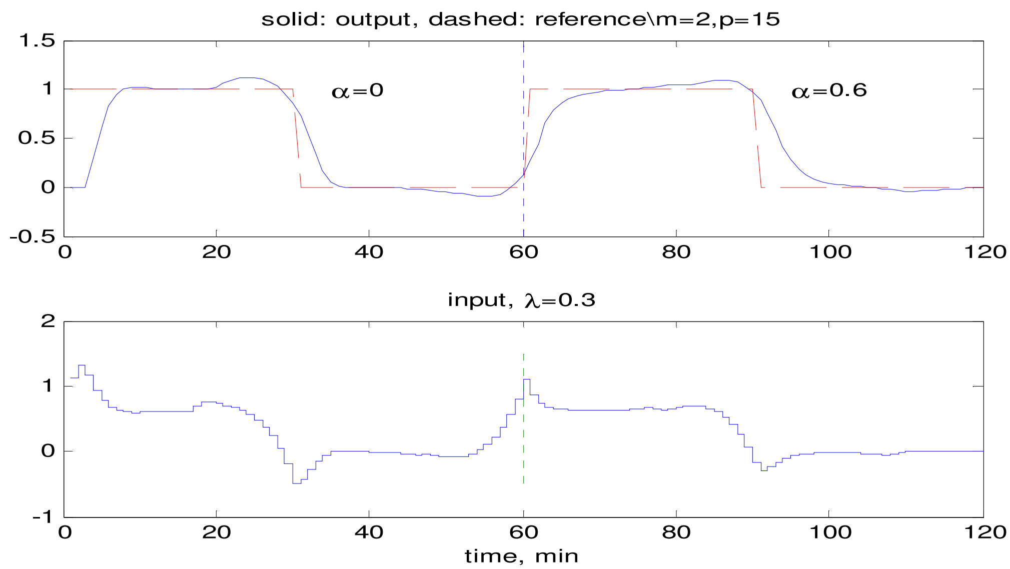


Fig 7.12 Response for m=2,p=15

From Fig7.8,Fig7.9 and Fig7.10 we can observe that at a constant prediction horizon 10, peak over shoot decreases when moving horizon increases from 2 to 5.

From Fig7.8,Fig7.11 and Fig7.12 we can observe that at a moving horizon 2,peak over shoot increases when prediction horizon increases from 5 to 15

7.3 Step response model of water heater responses with and with out set point predection

For m=2,p=10 and control weight 1

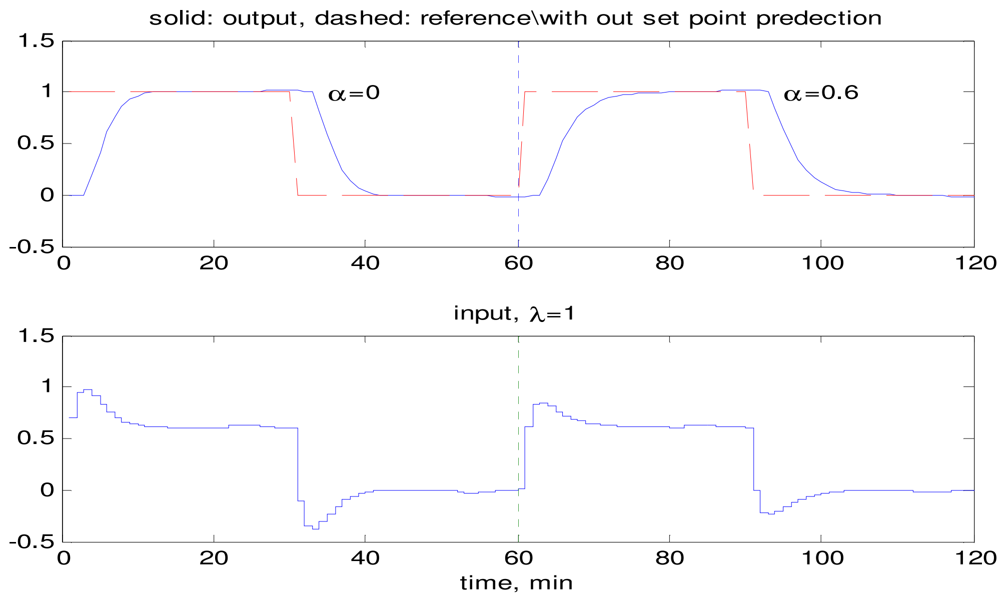


Fig 7.13 Response with out set ponit predection

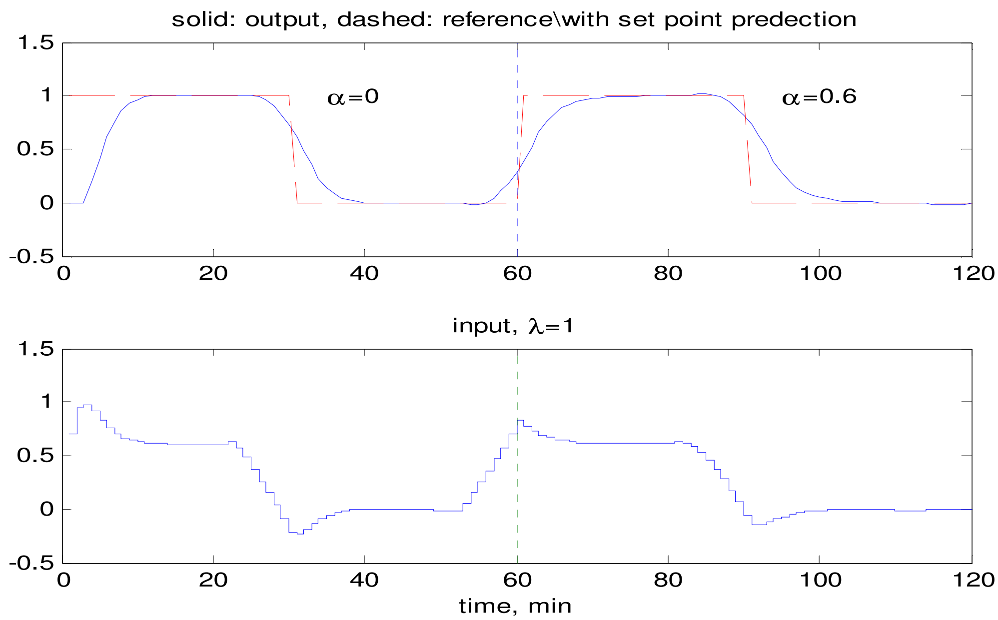


Fig 7.14 Response with set point predection

From above figures 7.13,7.14 we can observe that with set point prediction we get good response compared to without set point prediction.

7.4 Effect of a Smooting factor on Step response model of water heater response

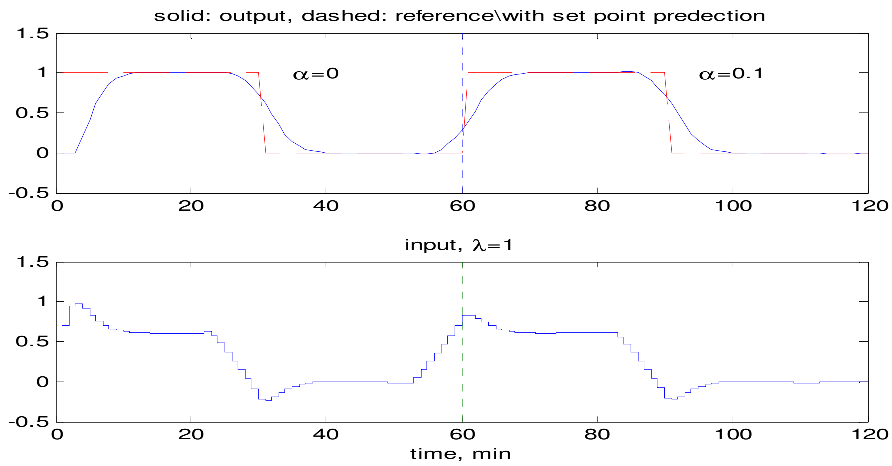


Fig 7.15 Response for smoothing factor 0,0.1

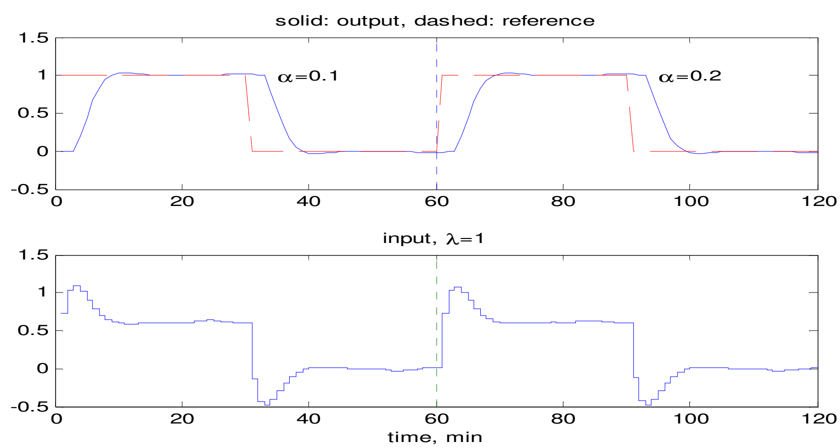


Fig 7.16 Response for smoothing factor 0.1,0.2

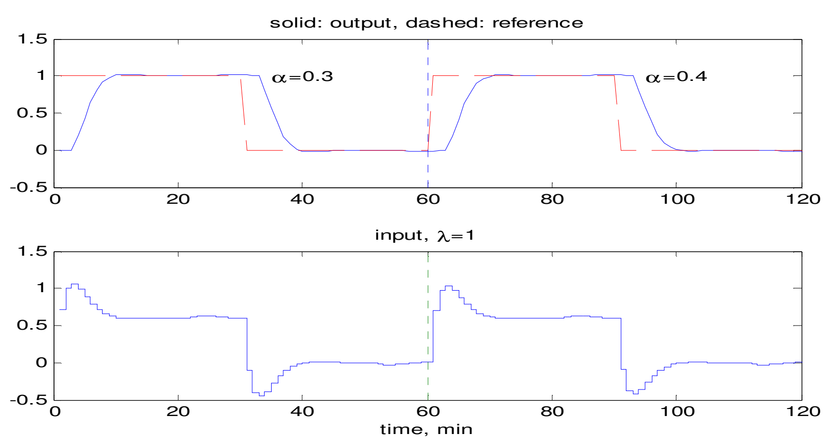


Fig 7.17 Response for smoothing factor 0.3,0.4

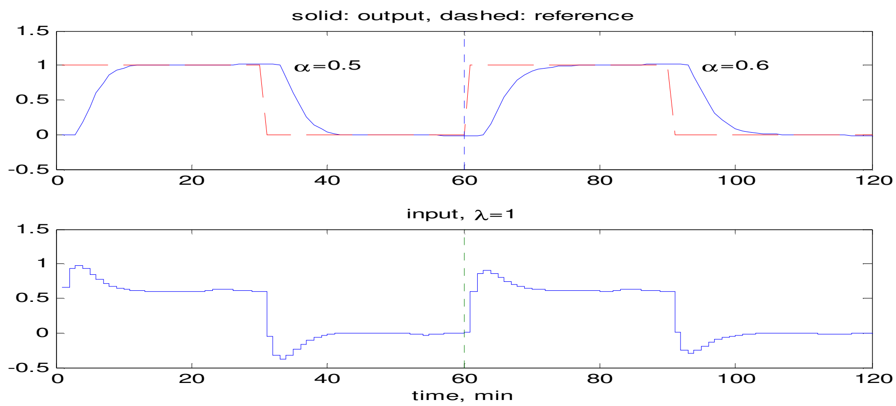


Fig 7.18Response for smoothing factor 0.5,0.6

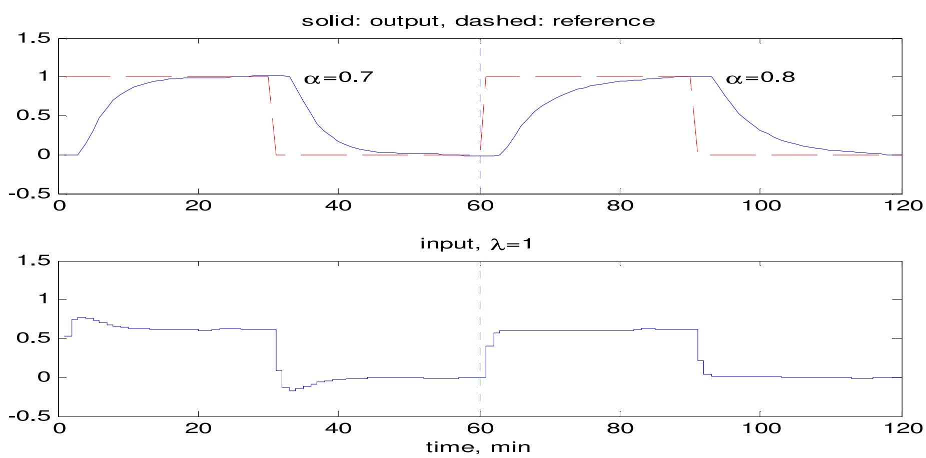


Fig 7.19Response for smoothing factor o.7,0.8

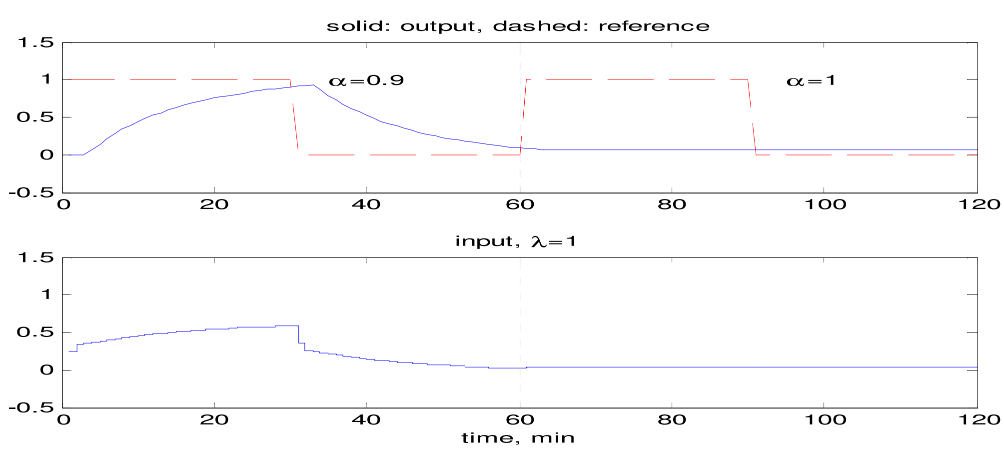


Fig7.20Response for smoothing factor 0.9,1

From Fig 7.15 to Fig 7.20 we can observe that water heater response affected by smoothing factor.

CHAPTER-8

CONCLUSION AND FUTURE WORK

8.1 CONCLUSION

First we study about distillation column, in the case we analyzed with the help of McCabe Thiele method easily find out the number of tray of tray type distillation column. In control strategy we analyzed in case of upset feed, feed have linear relation with both distillate and vapour, but in the case of upset feed composition feed composition and distillate have linear behavior throughout, but in the case of feed composition and vapour starting have nonlinear after some duration it got linear. For control distillation column we used model predictive control it give good performance especially in multivariable process, till now model predictive control face tuning performance, it give better performance than PID controller. With the help of model predictive control we can easily impose constrains.

The effect of DMC tuning parameters for Step response model of water heater observed that when the moving horizon increases at a constant prediction horizon peak over shoot decreases, at a constant moving horizon peak over shoot increases with prediction horizon

The effect of control weight on step response model of water heater is observed that ringing occur for without control weight, ringing can be decreased by increasing the control weight as required.

8.2 Future work

DMC tuning setting is not give always good performance some modification need in DMC tuning setting. Model predictive control is based on model, another type of model also we can use state space model, neural network, fuzzy logic.

Further work is required to be done towards the application of this method to constrained systems of Multiple Input Multiple Output (MIMO) systems.

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